ASSESSING THE INCOME AND SUBJECTIVE WELLBEING RELATIONSHIP ACROSS SOUTH AFRICAN DEVELOPMENTAL CONTEXTS: A MULTILEVEL ANALYSIS FROM 2008 TO 2017

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Introduction

As developing countries strive to achieve wellbeing standards similar to those of developed countries, it is necessary to consider the relationship between happiness, life satisfaction, depression and economic development. Standard Utility theory asserts that higher income leads to higher utility and therefore increased welfare. It is then logical to assume that higher income would be associated with increased happiness. Studies confirm this with findings of higher average happiness observed in developed countries in comparison to developing ones (Myers & Diener, 1996). However, recent studies report rising depression levels in developed countries above those exhibited in developing countries (Mojtabai et al., 2016) (Warshaw et al., 1991). This seeming contradiction suggests a more complex relationship between income, depression and happiness than anticipated. Furthermore, this shows that greater income and economic development is not the simple panacea for unhappiness but could, in fact, defeat mankind's primary objective – the pursuit of happiness. This warrants a deeper understanding of the impact of economic development on happiness, which is a critical aspect of development policy.

South Africa has significant levels of inequality expressed through race and consequently through spatial patterns of residence as a legacy of apartheid and colonialism (Lester et al., 2000). Apartheid was racial segregation that was institutionalised in South Africa from 1948 until the early 1990s. Apartheid policies barred individuals of colour from full labour market participation and the enjoyment of civil liberties. This resulted in differentiated public-good provision, with systematically lower provision for non-whites with emphasis on blacks. Non-whites received lower levels of education, housing, healthcare provision, and other public goods (Cole et al., 2018) thereby suppressing their socio-economic development and their subjective wellbeing (SWB) (Bookwalter & Dalenberg, 2010). The differentiated public good provision policy was expressed through racial residential segregation resulting in spatial inequalities. Residential segregation occurred in both urban areas with the development of townships, as well as in rural areas with the creation of Homelands (Lester et al., 2000). As such, spatial inequalities occur across and within the rural-urban sectoral divide.

Post-apartheid reform policies were geared toward income redistribution and the provision of public goods in an attempt to redress the inequalities caused by apartheid. However, reform is mostly targeted at urban areas, under-treating rural areas such that spatial inequality patterns exist at the level of the rural-urban divide (Noble & Wright, 2013). For this reason, the rural sector exhibits systematically higher levels of deprivation than the urban sector. This deprivation takes place in both income (money-metric) terms and non-income (capabilities) terms. This translates into lower levels of goods and services consumption in rural areas yielding lower wellbeing. For this reason, we anticipate lower SWB in rural areas, and the income SWB relationship to be confounded by non-income deprivation. Studies focusing on income and

SWB differences across the rural divide find differing outcomes. Lenzi & Perucca (2016) find that people in urban areas had higher SWB than in rural areas, but rural areas embedded in urban sectors had higher SWB than those outside of the urban sector. Studies from developing countries such as Thailand and China found no difference between SWB across the rural and urban sectors (Davey et al., 2009; Pholphirul, 2014).

However, there may be mitigating factors which influence the income and SWB relationship. These include differences in the level of competition across sectors, with higher competition characterising urban settings (Knight & Gunatilaka, 2010). Differences in one's worldview and the nature of work, were found to dominate the SWB considerations of the rural Americans over objective considerations of their economic conditions, such that SWB is higher than expected give economic conditions (Gimpel & Karnes, 2006). For these people, their world view and lived experience insulated them from objectively established economic deterioration in their places of residence. Rural dwellers in the EU were found to have higher SWB for which social capital partially determined (Sørensen, 2014).

Existing literature in the South African context accounts for individual and household level unobserved effects, finding positive income effects with significant and large relative effects (Kingdon & Knight, 2007; Posel & Casale, 2011). Given the diversity in developmental contexts across South Africa, we are interested in determining the income and SWB relationship across developmental contexts, spanning over the rural-urban divide. To uncover this, it is necessary to account for environmental context. Although the studies cited were carried out at the municipal level, they failed to account for municipal developmental contexts. In a contextual study across China, Wu & Tam (2015) found different income effects on wellbeing as district economic development changed. They found a positive income effect in lower-income areas and a negligible effect in high-income areas. This study indicates that the magnitude of the relative income effect concerning the absolute income effect is affected by the influence of socio-economic factors that are subject to change in each context. The resulting relationship between subjective wellbeing and the total income effects may be influenced by these underlying dynamics.

As such, differences in environmental characteristics such as growth rates, wealth distribution, work-culture and other unobserved factors may influence the relationship between socioeconomic status and subjective wellbeing (SWB)/happiness. For the true relationship in each context to be unearthed, it is necessary to control for confounding environmental factors. This can be achieved by contextual analysis (Ferrer-i-Carbonell, 2005; Wu & Tam, 2015).

We investigated the dynamics of subjective wellbeing and income effects given spatial socioeconomic inequality in post-apartheid South Africa using the National Income Dynamics Survey (NIDS) data from 2008 to 2017. We also used municipal data from the EasyData repository. Using these data, we were able to analyse the individual, household and district municipal levels forming a clustered structure, which locates each level of analysis as a sub-group of a higher one. Factors at each level not only exert their effect but interact with factors at other levels to exert a further separate influence. It was necessary to adopt a statistical model which allowed us to model such interdependence in our data. To this end, we employed multilevel modelling to account for the clustered structure of our data.

Socioeconomic development grouping was performed using principal component analysis (PCA). This method allowed us to generate a socioeconomic development index that is weighted on a range of socio-economic development factors to rank municipal development. Municipal districts were thus ranked by how well they scored on a weighted average of socioeconomic factors instead of a single factor. This was done to provide as robust a classification as possible. From this point, we conducted our multilevel regression analysis.

The structure of this paper is as follows: we start by surveying studies from international and local literature. This is followed by our Data and Methodology section which provides a detailed outline of methods used in this study. This is followed by the presentation of our results. Finally, we conclude with a brief discussion of our findings

Literature Review

Theoretic Literature Review

Standard preference theory conceives of utility as being positively related to consumption. The higher one's consumption as afforded by their income, the higher their utility. As income increases past a point of subsistence/satiation consumption, successive increases yield decreasing increments in utility. In this standard formulation of utility, one's enjoyment of goods and services consumed is the only material factor. However, this is an incomplete view of utility and must be accompanied by an explanation of relative preference theory.

Relative Preference theory developed as a parallel theory to Contrast theory in psychology. This theory first formulated in Duesenberry (1949) expands upon normative utility theory by introducing relative effects to utility valuations. Relative preference theory asserts that an individual's utility function comprises both an absolute and a relative component. The relative component is derived from an individual's consumption level in comparison with the surrounding members of their social group. While goods may endow absolute utility based on their intrinsic value to an individual, an alternative source of utility is experienced from the comparisons made with some reference group. This may be induced through a mechanism of positive comparison with the reference group like the prestige gained from conspicuous consumption (Veblen, 1899). These effects from comparisons made with other individuals are termed relative effects. Relative effects account for the phenomenon that individuals assign value according to comparisons with some reference group. Duesenberry's specification in (Duesenberry, 1949) comparisons only were made upwards such that utility was negatively determined by relative effects. The combination of both components of utility theory is understood to exert a total effect on the outcome. We assume that happiness is similar to utility which allows the exposition of the parallel Endowment contrast model.

Tversky and Griffin's (1991) model of Endowment and Contrast (E-C) unifies two competing mechanisms driving SWB evaluations. The E-C model is an extension of Dusenberry's Contrast theory, where contrast effects are thought to interact with endowment effects, in determining an individual's subjective wellbeing. Hedonic psychology and economic theory both forward notions of diminishing absolute income effects. For the economist, satiation was the cause arising from a fixed resource for processing material consumption e.g. one's appetite. For the psychologist, the utility was thought to diminish through the individual's automatic recall of past events with which he compares his present experiential endowment. This phenomenon is termed "Hedonic Treadmill theory" (Brickman & Campbell, 1971) or "preference drift" (Groot & Maassen van den Brink, 2000). Past experiences would thus operate as a baseline of comparison which the individual would use to evaluate the present wellbeing.

E-C theory differs from relative utility theory in its conception of relative effects. In the E-C model, comparisons can be made upwards or downwards exerting a positive or negative effect on SWB. The model recognises the direct effect of endowment and both the direct and indirect effects of contrasts with the past on a present experience's wellbeing evaluation (Griffin & Gonzalez, 2013). As such, the endowment component can be interpreted as the marker for absolute benefits from an experience while contrast is the marker of relative benefits from an experience. The main difference between this model and relative preference theory is in terms of how relative effects are parsed out. Relative effects from contrasts with other individuals contribute towards contrast effects. However, contrasting with one's past expressed as a diminishment in absolute income is parsed out as a separate contrast effect. Thus, contrast effects account for what is termed relative effects and diminishing marginal utility. Endowment accounts for the part of absolute income before diminishing returns occur.

Empirical literature review

The most famous study in which relative preference theory is invoked is presented in Easterlin's (1974) paper. This renowned paper stimulated a debate in wellbeing literature when he found that over time there has been a glass ceiling on happiness while income has risen. These findings were explained by the interaction between two mechanisms: the hedonic treadmill theory and relative preference effects. Below subsistence levels of consumption, income is a significant determinant of wellbeing as consumption at this level goes towards survival. Above the point of subsistence/satiation other factors such as emotional and social fulfilment weigh greater (Lane, 2000). Increasing average incomes past this level causes absolute income effects to diminish, such that relative income effects account for larger weighting in SWB ratings. The gap between income classes is reduced and SWB in higher-income classes loses to diminishing contrasts with those below. With absolute effects and relative effects simultaneously diminishing, the total effect of income on happiness falls. Thus, rising income was found to be ineffective at rising SWB over time. Given the *a priori* expectation that increasing income increases happiness, this finding was dubbed "The Easterlin Paradox". The above explanation assumes increases in income are at least evenly distributed amongst income classes. Significant research on income inequality disproves such a simplifying theoretic assumption (Birdsall et al., 1995; Ray, 2010).

Easterlin (1974)' s study employed the following methods of analysis: a within-country cross-section, a between-country cross-section and time series analysis at the country level. For the within-country cross-section, different countries were surveyed and the findings have been supported by those of later studies such as those by (Clark & Oswald, 1994), (Clark, 2016) and (Frey & Stutzer, 2000). However, cross-sectional analysis between countries finds no relationship between happiness and income as is echoed by (E. Diener et al., 1999). A modest relationship was found by Easterlin for time series within a single country. This result showing no relationship between income and happiness has been termed the Easterlin paradox (Easterlin, 1974).

There exists a counter-literature which disputes the existence of the Easterlin Paradox. Authors of this literature insist that absolute income effects dominate relative effects. Stevenson & Wolfers (2008) argue that there is, in fact, a positive relationship between income and happiness, thus opposing the Easterlin Paradox. Stevenson and Wolfers (2008) analysed the relationship between GDP and subjective wellbeing between individuals in a country, between average happiness levels between countries and as a time series. They found a positive effect of GDP per capita in all cases. However, while a positive relationship is reported for the time series analysis, it is modest. The authors thus find no evidence for a dominating relative income effect, whereas the modest time-series relationship may be evidence for the hedonic treadmill such that some relative effects may be present. Hagerty and Veenhoven_(2003) also find a positive effect of income on happiness. Their study employs a longer time series and a broader survey across countries than that of Easterlin (1974) to yield the result of a positive impact of income on happiness across countries. Income is found to have a larger effect in the short-term but diminishes over the long term supporting the hedonic treadmill theory.

How should these conflicts within the literature to be interpreted? Clark et al. (2008) clarifies the difference in findings subject to methodology by illustrating the dynamics between absolute income and relative income effects over time. Starting at a period in which there are large gaps between income classes in a single country, there will be an apparent positive effect of income-driven by both absolute income and relative income. Over time, the flow of income and income distribution changes such that gaps between income classes are diminished causing the relative income effect to mute the absolute income effect. Where a relationship between income and SWB exists at a single point in time, it is diminished over time. For this reason, studies employing time series methodology fail to find a relationship in the long-term or find a modest one. While time series analysis may be inadequate, panel data techniques may be better suited at isolating time-variant effects.

Ferrer-i-Carbonell and Frijterts (2004) found that controlling for time-invariant fixed effects reduces the impact of income by two-thirds. So, while time-series regression may find evidence of income effects, these may be overstated when unobserved fixed effects are not accounted for. Accounting for such fixed effects is necessary to uncover the true long-term relationship between income and happiness. Panel data techniques allow for time-based variance of data as well as for the control of observed and unobserved fixed effects. This enables the exposition of the income and happiness relationship over time and correction for fixed effects. Studies have found evidence for both sides of the debate. The findings of Mentzakis and Moro (2009), who employed panel data analysis on British data ranging from 1996-2003, supported the Easterlin Paradox by indicating that relative income is more impactful at higher income levels. These findings are echoed by Diener et al. (1992) who notably found income effects to be independent of the developmental context across the U.S.

Panel data studies in developed countries have also found a positive relationship between income and happiness (van Praag et al., 2003). Ferrer-i-Carbonell and Frijters (2004) demonstrated that individual fixed effects greatly impact the results of a given study. Blanchflower and Oswald (2004b) found a positive relationship between income and happiness in the USA and Britain once individual traits were accounted for.

In recent years, studies which go a step further than panel data techniques have been conducted. These studies seek to control for environmental context to account for unobserved environmental factors in addition to individual factors. Di Tella et al. (2003) demonstrated the positive impact of income, additionally illustrating that broader environmental context, such as macroeconomic variables, influence individual happiness ratings across countries over time. Ferrer-i-Carbonell (2005)'s study found the impact of income to have been greater for East Germans who were poorer than on their more affluent West German counterparts. This study controls for unobserved effects by controlling for the development context. Developing world studies which contextualize health and SWB on some reference group including (Hongbin & Yi, 2006; Wu & Tam, 2015) both finding dominance of relative income on SWB and SRH.

Fei Wu & Tam (2015) notably build on the E-C model to explain the differing effects of socioeconomic status on SWB at different levels of economic development. Their findings show that at higher levels of so SES, in a context of higher regional economic growth, there are reductions in household-level SWB evaluations. This suggests that in contexts with higher levels of regional economic growth, increases in SES are contrasted with those of households around them to diminish the gains from the endowment in greater SES. This indicates a dominance in the relative effect of income past a threshold level.

Evidence from South African Studies

A broad literature on income and happiness already exists in South Africa. What is apparent in this literature are the findings unique to South Africa showing race and ethnicity to be substantial determinants of SWB. Income is generally found to be positively related to SWB in South Africa (Blaauw & Pretorius, 2013; Cramm et al., 2010; Kingdon & Knight, 2007; Kollamparambil, 2019; Posel & Casale, 2011).This relationship endures in both cross-sectional (Blaauw & Pretorius, 2013) and panel studies (Kingdon & Knight, 2007; Kollamparambil, 2019; Posel & Casale, 2011). It is unclear whether this positive relationship is explained by a dominance of absolute effects (Kollamparambil, 2019) or relative effects (Kingdon & Knight, 2007; Posel & Casale, 2011). In this review, we highlight important factors that possibly obscure econometric analysis in the South African setting.

South Africa is a middle-income country with high levels of income and wealth inequalities (Leibbrandt et al., 2012) and 50% of the population lives in poverty (Francis & Webster, 2019). There is an estimated global subsistence/satiation level US$10 000 (Frey & Stutzer, 2002). This compared to a GDP per Capita of US$ 6451.12 (www.worldbank.com) on average in South Africa between 2008 and 2017 suggests that the hedonic treadmill hasn't taken effect yet. For this reason, we expect a strong and significant impact of absolute income effects on average. We note that such an expectation is overly determined by an understanding of financial means as a substantial method of raising wellbeing. A competing view instead locates basic capabilities as determinants of wellbeing especially at low-income levels (Klasen, 2000). Access to basic goods, such as housing, water and electricity, have been found to exert a substantial impact on wellbeing and subjective wellbeing at low-income levels across South Africa (Bookwalter & Dalenberg, 2010). Research has shown that income is a poor predictor of wellbeing deprivation amongst South Africa's poor, signalling a divergence of income from wellbeing (Klasen, 2000). Kollamparambil (2019)'s finding that happiness inequality has been falling despite rising income inequality illustrates the divergence of income from SWB at the country level. As such, public good provision of basic goods may bear a greater effect on subjective wellbeing than actual income earned.

We first consider the relationship between public goods and SWB in this setting looking first at Absolute effects and then Relative effects. Increases in Absolute income are expected to increase non-income consumption of basic goods leading to higher levels of wellbeing (Bhorat et al., 2014; Klasen, 2000). These increases in wellbeing are expected to raise SWB (Bookwalter & Dalenberg, 2010). We anticipate absolute income effects to be muted by public good provision in low socioeconomically developed contexts. Absolute income effects in highly socioeconomically developed places are expected to be substantially larger given the increased spending capacity of income derived from developed environments.

Different consumption domains operate differently (Wang et al., 2019). There are differences between relative effects from public good consumption versus private good consumption, with the latter exerting greater relative effects Galbraith (1958). Given that public goods are non-rivalrous we postulate that they exert very small relative effects with the same relative income group. Kaus (2013) shows that South African households are more interested in perceived relative income standing rather than absolute income standing in their social group. As the average income of poor households increase, households are induced to increase spending on visible goods. For this reason, even poor households dedicate a portion of income towards visible goods. Even in the face of substantial dependence on public good provision, there is scope for significant relative effects to be derived from conspicuous consumption.

With the above discussion in mind, we examine the nature of income effects on SWB. We begin with a look at the possible absolute income effects contingent on socio-economic development. Public good provision is less important in richer areas as affluent individuals resort to the market for the attainment of basic goods. Even though the rich are reliant on public goods, their nature of "needs" preference profile changes such that there is a preference drift in publicly provided services. At higher levels of income road infrastructure, education and sanitation are important (Bookwalter & Dalenberg, 2010). This preference drift results in higher-order needs which contribute less to absolute income effects than basic needs. Thus, the Hedonic Treadmill theory applies to both private income and public goods. For this reason, we expect generally diminishing absolute income effects for richer contexts.

Differences in public good provision at the level of the rural and urban divide result in systematic differences between rural and urban public service access (Noble & Wright, 2013). South African rural areas are found to have lower public good provision. These areas also have higher levels of non-income deprivation (Klasen, 2000). Income poverty is also present since it is a close correlate of non-income deprivation. The poorest South Africans are found in rural areas (Bhorat et al., 2014; Klasen, 2000). Individuals are found to experience higher SWB in studies such as (Knight & Gunatilaka, 2010; Sørensen, 2014). Yet, studies such as (Davey et al., 2009; Pholphirul, 2014) find no significant difference across the sectoral divide. Determining which scenario applies to South Africa will be dependent on assessing the income and SWB relationship within the context of the developmental environment. We briefly consider the dynamics of absolute and relative income effects across the rural-urban divide.

We use the "human needs hypothesis" (Diener & Biswas-Diener, 2002; Diener & Lucas, 2000) to explain our anticipation of lower absolute income effects in rural areas. This hypothesis postulates that income is only useful to the extent that it provides basic goods. To the extent that income is limited in its ability to provide access to basic needs, its effect on SWB is severely limited. Given that public services are underprovided in rural areas, basic needs are attained through market provision. Incomes earned by the poor may be too low to access market provision of basic needs. As such incomes are ineffective at attaining basic needs yield low Absolute income effects towards SWB.

Relative effects in rural areas may be large and positive. This would be due to rural areas having less competition leading to a less stressful environment (Knight & Gunatilaka, 2010). This less stressful environment may better facilitate marriages thereby increasing pleasure and leading to higher SWB (Pholphirul, 2014). Differences in reference group formation have been found to differ between urban and rural sectors (Knight & Gunatilaka, 2010). Rural dwellers tend to select their immediate social group as their reference group. This leads to limited information sets upon which comparison are made resulting in a greater propensity for comparisons to be made against similar people. Furthermore, Wang et al. (2019) find that increases in the incomes of individuals of similar gender, education and age in the local community lead to increases in SWB. Increases in similarly defined individuals' incomes from different communities lead to decreases in one's SWB.

Differences in work culture and the meaning of work lead to differences in SWB through increased work satisfaction. Rural dwellers in America are said to consider themselves as part of the *petit bourgeoisie*, and not as labourers (Greenberg, 1981). Such feelings may be associated with an understanding of being more self-sufficient and pride which may ultimately result in a divorce of perception about their circumstances from the reality (Gimpel & Karnes, 2006). This may also point to a general divergence of lived experience from objective statistical figures.

Increases in wealth relative to the surrounding village may lead to increases in social capital which was found to be a stronger determinant of SWB in rural settings across Europe (Sørensen, 2014). Anderson et al. (2012) find sociometric status to be a strong predictor of SWB. To the extent that increases in income status may increase social capital in one's social group through sociometric status, we anticipate positive relative effects in rural areas.

Given the racial nature of apartheid, discrimination inequality is mapped by race and space such that races are clustered in socioeconomically homogenous residential areas across the rural-urban divide. To this end, race may work as its reference group eliciting different effects than a more secular framing of reference. Kaus (2013) finds that blacks spend more of their income on conspicuous consumption than whites indicating high aspirations amongst blacks. This suggests that blacks hold other blacks as their main reference group in which negative contrasts are made. Neff (2005) introduces ethnicity as a unit of analysis as opposed to race. Racial categorizations are said to mask relevant factors such as differing conceptions and determinants of SWB. This inclusion of racial differences ultimately allows for the inclusion of intra-racial differences. Moller and Saris (2001) also acknowledge the existence of differing domain satisfaction affecting wellbeing differently across races. They also found that the future was a larger predictor for blacks and whites rather than current domain satisfaction. The above studies point to the variation amongst South African races and ethnicities concerning which groups' reference formation is conducted as well as what domains comparisons matter most. Race is expected to contribute a significant influence on both absolute and relative income effects.

Differences in the level of basic needs met by public good provision will determine the nature of income effects in each context. Residential segregation clusters people by race (Cole et al., 2018) and socioeconomic status. Rural areas experience lower levels of public good provision as compared to urban areas (Eastwood & Lipton, 2004). As such Rural areas are found to have considerably lower levels of wellbeing than even low-income areas in urban areas (Bhorat et al., 2014; Klasen, 2000) Such disparities are only magnified by the practice of residential segregation. This is evidence of clustering of residential segregation resulting in black residential areas exhibiting lower wellbeing and therefore SWB. Residential segregation occurs at the level of rural and urban sectors as well as within each of these sectors. Lower public good provision may lead to overall lower SWB if income earned can't provide access to basic goods. However, it may also be the case that people in rural areas are happier due to lower levels of competition and preference drift (Perruca, 2016). While the exposition of absolute and relative income dynamics is conducted mainly from the viewpoint of intra-urban residential demarcations, the same analysis applies to the interaction between urban and rural sectors.

Spatial inequalities enforced through residential segregation may act to insulate reference formation to those in one's immediate surrounding. People tend to carry on their daily lives in geographically limited areas such as those demarcated by residential areas and district municipalities (Pattie & Johnston, 2011). Such geographical limitations may limit an individual's exposure to inequality. As such, the lived experience of inequality may scarcely resemble actual levels of measured inequality in a society (McLennan et al., 2016). McLennan et al. (2016) found the highest exposure to other income classes in the metropolitan municipalities of the City of Cape Town, City of Tshwane, City of Johannesburg and Ekurhuleni. With this in mind, reference formation is likely to be focused on local reference groups and partially on the greater income distribution in South Africa (Kingdon & Knight, 2007; Posel & Casale, 2011). We define these relational dynamics to be comprised of relational spheres ranging from proximal (or local) to distal (or global). For this study, we locate the local sphere as the district municipality and the global sphere as the entire country.

Given the different spheres of reference formation, just how might contrasting play out according to relational proximity? The effects of material inequality and relational effects on happiness considerations may be significantly altered by the extent of community spirit. This can be understood as the level of individualistic culture that exists within a community. The externalities endowed by communities on disadvantaged members are through social institutions and norms. An example is risk-sharing schemes within communities which may work to ensure that higher levels of consumption are attained by indigent members thereby increasing their wellbeing. These positive externalities from the surrounding community may also raise subjective wellbeing through positive affect experienced from social cohesion in poorer communities which tend to be less individualistic, illustrating the value of social capital (Helliwell 2001) Cramm et al. (2010) found income to be a positive predictor of subjective wellbeing in the Eastern Cape and that social capital is also important for all income groups.

Posel & Casale (2011) investigated the difference between objective and relative ranking of an individual's socioeconomic status and how this impacts SWB. They found a positive income effect, but perceived relative ranking has a greater effect on SWB than their actual objective ranking. This finding was also found to be dependent on spatial and relational proximity of the reference group. This supports the findings of Kingdon & Knight's (2007) study, which investigated the impacts on the SWB of different reference groups of comparison. Increases in the income of immediate neighbours resulted in positive impacts on SWB while negative for further neighbours and across racial groups. This illustrates the role which race, and spatial inequalities play in influencing absolute and relational effects. Only through controlling for environmental context at the level at which communities form can the confounding factors be accounted for. The current South African literature lacks studies that control for both individual-level and community-level fixed effects. The purpose of the current paper is to address this vacuum by conducting such a study. To this end, we employ a multilevel model which observes the income happiness relationship against contextualised on district municipality socioeconomic growth.

Data and variable selection

The dataset employed is the National Income Dynamics (NIDS) dataset (Southern Africa Labour and Development Research Unit (SALDRU), University of Cape Town) for the period 2008 to 2017. The NIDS dataset is a nationally representative survey conducted at the household level containing both household and individual-level data points (www.nids.uct.ac.za). Data on municipal variables were gathered from the EasyData repository (Quantec, South Africa) which provides economic data for South Africa. From this dataset, we sourced data for all 52 district municipalities in South Africa for years corresponding with the NIDS waves[1].

The datasets mentioned account for data clustered at three levels. The first is that of the individual, and the second is that of the household and the third is the district municipality. A desirable feature of the NIDS dataset is that all individuals are assigned to a household and grouped with other individuals belonging to that household. We merged all the datasets using the year and municipal districts as our time and panel identifiers respectively. This allowed us to assign each household its district municipality. The resulting dataset contains individuals nested in households and households nested in district municipalities with variables tracked over time justifying the use of multilevel modelling.

Individual and household-level variables

Our dependent variable was current individual satisfaction which is rated using the Satisfaction With Life Scale (SWLS) developed by Diener et al. (1985). The SWLS is an interval scale that is proving to be more reliable than other single item scales and is thus favoured for the current study. Such a measure is considered reliable in the sense that it exhibits greater temporal stability, high internal consistency and high convergence with other wellbeing measures (Larsen et al., 1985). In the NIDS dataset 'satisfaction' or 'subjective wellbeing (SWB)' is coded as an answer to 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?*" (Emmons & Diener, 1985). On average the individual satisfaction level in our sample is 5.3 varying slightly between developmental contexts. Notably, satisfaction is higher on average in the lower developmental category with an average of 5.9.

We employ two independent variables as our target variables, namely; absolute income and relative income. Our variable for absolute income is based on monthly household income per capita (with no imputations) which enters our model in logarithmic form. Our decision to use household per capita income is based on the rationale that pooling of incomes is a common risk-sharing method used in impoverished communities such that happiness may be raised by other people's incomes (Kingdon & Knight, 2007).

Relative income is modelled using subjective relative income. For relative income, respondents were asked *"How would you classify your household in terms of income, compared with other households in your village/suburb?"*. This question measures each individual's perceived economic ranking as opposed to their actual ranking, when their income is compared to that of their peers.

[1] With exception to the data on poverty rates and formal housing which was only available for a limited selection of district municipalities.

Table 1: Summary statistics of individuals and household variables according to socioeconomic development categories[2]

Variable	Overall		High developed municipality		Low developed municipality	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Individual factors[3]						
Male						
0 (No)	5418	51.47	1402	51.47	1390	53.83
1 (Yes)	1025	48.12[4]	1322	48.53	1192	46.17
Black						
0 (No)	2120	20.3	806	29.59	364	14.1
1 (Yes)	8323	79.7	1918	70.41	2218	85.9
Age (Mean±SD)	10443	35.97±11.16	13281	34.97±11.35	2582	37.40±11.53
Age squared (Mean±SD)	10443	1395.54±883.13	2724	1347.70±862.09	2582	1531.63±906.98
Married						
Unmarried	7242	69.35	2017	74.05	1618	62.66
Married	3201	30.65	707	25.95	964	37.34
Education Level						

[2] All statistics reported in this table are unweighted

[3] All statistics reported in this table pertain to the subset of observations included in this paper's regressions.

[4] The values for this column regarding gender don't add up to 1oo% due to rounding errors. We round off to two decimal places.

No Matric	8173	78.26	2139	78.52	2114	81.87
Matric Certificate	1691	16.19	439	16.12	349	13.52
University Degree	579	5.54	146	5.36	119	4.61
Satisfaction Level						
1 (Very Dissatisfied	562	5.38	111	4.07	163	6.31
2	559	5.35	115	4.22	137	5.31
3	1064	10.19	304	11.16	254	9.84
4	1397	13.38	399	14.65	334	12.94
5	2033	19.47	507	18.61	512	19.83
6	1386	13.27	397	14.57	348	13.48
7	1306	12.51	374	13.73	319	12.35
8	1088	10.42	282	10.35	245	9.49
9	377	3.61	90	1.3	85	3.29
10 (Very Satisfied)	671	6.43	145	5.32	185	7.16
Household-Level Factors						

LnHousehold Income per Capita (Mean±SD)	10443	7.35± 1.26	2724	7.57± 1.11	2582	7.23±1.19
Household Income per Capita (Mean±SD)	10443	3388.46± 7884.02	2724	3834.66± 8020.35	2582	2893.60±10711.44
Relative Income						
Above Average Income	1264	12.1	333	12.22	297	11.5
Average Income	5013	48	1378	50.59	1205	46.67
Below Average Income	4166	39.89	1013	37.19	1080	41.83
Unemployed						
Employed	8105	77.61	2224	81.64	1957	75.79
Unemployed	2338	22.39	500	18.36	625	24.21
Religion						
0 (No)	926	8.87	260	9.54	209	8.09
1 (Yes)	9517	91.13	2464	90.46	2373	91.91
Healthy						
0 (No)	180	1.72	39	1.43	59	2.29
1 (Yes)	10263	98.28	2685	98.57	2523	97.71
Formal Housing						
0 (No)	2134	20.43	547	20.08	371	14.37
1 (Yes)	8309	79.57	2177	79.92	2211	85.63
Municipal-Level Factors[5]						
Average Household Income (Mean±SD)	10443	164337.1±91118.54	22724	267579.8±54715.55	2582	37796.56±14135.56

[5] All statistics reported for municipal level factors represent the average value or proportion of each factor as found across district municipalities.

LnGRP (Mean±SD)	10443	12.23±0.79	22724	12.94±0.19	2582	10.95±0.31
Population(Mean±SD)	10443	3061422±1424094	22724	4541214±572036.5	2582	821877.8±110436.2
Gini Coefficient (Mean±SD)	10443	0.64±0.30	22724	0.62±0.28	2582	0.67±0.36
Average Dependency Ratio(Mean±SD)	10443	42.47±3.42	22724	41.2±2.41	2582	46.15±4.31
Unemployment Level (%) (Mean±SD)	10443	24.01±4.77	22724	24.47±4.22	2582	25.27±6.48
Crime (Mean±SD)	10443	1005.71±552.6024	22724	1554.54±376.13	2582	375.1±88.59
Food Poverty Line (Mean±SD)	10443	347.30±59.43	22724	383.84±41.06	0	
Water Access (Mean±SD)	10443	0.16±0.05	22724	0.16±0.01	2582	0.12±0.09

Control Variables

For our control variables, we use individual and household level variables. Age is thought to be a significant determinant of happiness with a postulated "U shape". This is best evidenced by the positive relationship between age squared and happiness found in developed countries as found in studies like (Blanchflower & Oswald, 2004a). This U-shape is explained by the economic rationale that midlife is the point at which wages peak for most people, increasing satisfaction along with it (Steptoe et al., 2015). The average age in our sample is 36 years, with 50% of the sample less than 34 years old reflecting South Africa's youthful population. We expect to find a U-shape in our current context as borne out by previous studies such as (Kollamparambil, 2019). Possible reasons for this are contrary to the standard reasoning that life experience brings an appreciation for non-material factors and thus, as one ages less emphasis on wealth becomes the cause of increases in happiness. However, in the South African case, we expect the dip in the U-shape to occur at 60 when one qualifies for a state pension. This is often the first time many South Africans receive a regular income.

Education is expected to exert a positive effect on happiness exhibiting a positive gradient with higher levels of education attained (Blanchflower & Oswald, 2004b). The first effect of interest is an indirect effect expressed through the positive correlation and income through its ability to increase absolute income returns on the labour market. The effect of education on health and thus happiness is another causal path investigated by (Gerdtham & Johannesson, 1997) and (Bukenya et al., 2003) in developed countries. Education may also be a marker of unobserved individual factors such as motivation, intelligence and socioeconomic context, the latter for which this study controls. A high percentage of respondents in our sample lack matric degrees in either developmental context. There are more matric certificate holders in the high development category at 12% versus the 10% in low developed areas. A similar pattern ensues for university degrees as is expected given the country's low literacy levels.

Just about 80% of our sample falls under the category of "black" or African. Race is a significant and negative factor in the South African context (Ebrahim et al., 2013; Posel & Casale, 2011). This is due to the legacy of apartheid which imposed systematic socioeconomic underdevelopment of Africans. This suppression of socio-economic development factors that positively impact happiness is expected to reduce happiness in turn. In this way, race becomes a critical factor in the current context.

Thirty percent of our sample is unemployed. Unemployment results in a lack of labour market income, reducing consumption and decreasing happiness as a result. This negative effect is also brought about by a sense of isolation and a lack of purpose experienced by unemployed individuals. Clark (2003) points out that high levels of unemployment in a society may neutralize these negative effects, which will result in a limited negative effect on happiness.

Household size by number of residents, is employed as a proxy for a household dependency ratio[6]. The higher the numbers of residents and therefore the higher the expected dependency ratio, the lower average individual income as a share of household income (Fiegehen & Lansley, 1976; White & Masset, 2003). Income sharing is a common feature in South African Households where dependants are clustered in households with employed family members. As a result, household sizes grow and per capita income decreases exasperating economic circumstances. Household size is thus used as a proxy for employment dependency ratio as well as a predictor of poverty in its own right (Burns et al., 2005; Lilenstein et al., 2018). Through this mechanism, we posit that individual happiness ratings decrease as a function of household size. Formal housing is a variable included to operate as a proxy for essential household services such as water and electricity. In-house water access leads to greater sanitation resulting in higher health levels and thereby increasing happiness.

Some studies established religious belief as a positive contributor to happiness through its ability to ease emotional distress in the face of negative life experiences (Helliwell, 2003, 2006). South Africa is a broadly Christian country representing 84.2% of the population (Schoeman, 2017). Studies show no significant difference in SWB across religious denominations informing our choice to code religious belief as a binary dummy variable (Cohen, 2002; Ferriss, 2002).

Lastly, we include a control for marital status as a positive correlate of happiness. Marriage is coded as a binary dummy variable with 1 for "married" and 0 "otherwise". Marriage protects against loneliness which is linked to depressive episodes (Wei et al., 2005). Marriage was also found to increase sexual satisfaction as married people have more sex than those who are not and this increases SWB (Blanchflower & Oswald, 2004a).

Municipal Level Variables

Our municipal level data is gathered from the EasyData repository. This database combines multiple datasets collected from both public and private institutions. We include socioeconomic variables for all 52 municipal wards in South Africa, where available. The timing of data collection coincided with the NIDS waves, yielding datapoints for 2008, 2010, 2012, 2014 and 2017. This data was combined to form a panel of municipal level variables.

We included municipal level analogues for our individual and household level variables where possible. These included average annual household income, municipal unemployment levels and the average annual municipal dependency ratio. We added the municipal Gini coefficient as our objective income inequality measure with an average coefficient of 0.64. This figure approximates the level of 0.7 as found

[6] The number of residents is used to generate Household income per Capita

in previous literature (Alexander & Tredoux, 2010; Leibbrandt et al., 2012). Based on the findings of (Kollamparambil, 2019), we expected income inequality to be negatively related to satisfaction (Kollamparambil, 2019). We also included a poverty rate through the food poverty line which tracks the number of individuals earning less than R561 per month. This measure was used to indicate extreme income poverty. Water access is directly accounted for at the municipal level. We formulated the water access variable as a coefficient defined as: the number of households within a municipality which have water access / the total municipal population.

Population density was included to capture unobserved factors such as congestion and pollution levels. Higher population density increases pressure on the existing resource base resulting in environmental degradation and negatively affecting happiness (Ferrer-i-Carbonell & Gowdy, 2007). Congestion and pollution have also been shown to negatively impact happiness in these studies (Welsch, 2002, 2006). The municipal murder rate (annual number of murders) was included as a proxy for crime levels due to its positive correlation which other serious crimes. We favour utilizing serious crimes as our indicator of crime levels as petty/ less serious crimes are likely to be under-reported. Crime is expected to erode subjective wellbeing as it destroys a sense of security and therefore increases worry and anxiety (Powdthavee, 2005).

The Gross Regional Product (GRP) is a measure of the total value of goods and services produced within a municipality per annum. This is a municipal analogue of GDP and, as such, its growth rate can be viewed as an indicator of economic development. We used the logarithm of GRP to yield the growth rate. However, economic growth is only a crude measure of wellbeing and fails to account for many other environmental factors which may affect wellbeing through their ability to affect non-income consumption. Wu and Tam (2015), as well as Ferrer-i-Carbonell (2005)'s, are contextual studies in which money-metric variables such as GRP have been utilized as proxies for development. This paper seeks to improve upon such studies by conducting our analysis on an index of socioeconomic factors constructed through Principal Component Analysis.

Next, we explore our study methodology.

Methodology

Model Specification

Our study is concerned with the impact of our target variables contingent on developmental context. To achieve this, we interact with our target variables with a dummy variable indicating the level of municipal socio-economic development. The two development categories employed throughout are "Low Development" and "High Development". These categories are generated from an index which we detail in the Principal Component Analysis section of his paper. Our data analysis was conducted through a series of regression models beginning with a pooled OLS model, operating as our base model upon which all others are compared

$$1)\quad \mathrm{SWB}_{\mathrm{i\,t}} = \mathrm{B}_0 + \mathrm{B}_1 \log(\text{Household Income per Capita}_{\mathrm{i\,t}} + \mathrm{B}_2 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{Low Development}_{st} + \mathrm{B}_3 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{High Development}_{st} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t}} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t_{i\,t}}} \times \text{Low Development}_{st} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t_{i\,t}}} \times \text{High Development}_{st} + B_j X_{it} + \mathrm{U}_{\mathrm{it}}$$

$$\mathrm{i} = \text{individuals } 1, \ldots, \mathrm{n}\,,\ \mathrm{t} = \text{wave } 1, \ldots, 5,\ \mathrm{s} = \text{ district municipality } 1, \ldots, 52$$

This model failed to capture unobserved individual effects (A_{it}) which could bias our results. Therefore, we ran a fixed effects model to correct for this:

$$2)\quad \mathrm{SWB}_{\mathrm{i\,t}} = \mathrm{B}_0 + \mathrm{B}_1 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) + \mathrm{B}_2 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{Low Development}_{st} + \mathrm{B}_3 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{High Development}_{st} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t_{i\,t}}} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t_{i\,t}}} \times \text{Low Development}_{st} + \mathrm{B}_4 \text{Relative Income}_{\mathrm{i\,t}} \times \text{High Development}_{st} + B_j X_{it} + \mathrm{A}_{\mathrm{t}} + \mathrm{U}_{\mathrm{i\,t}}$$

We ran the random effects model to control for any observed time-invariant factors $\mathrm{Z_i}\gamma$ which may be correlated with the error term U_{it}.

$$3)\quad \mathrm{SWB}_{\mathrm{i\,t}} = \mathrm{B}_0 + \mathrm{B}_1 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) + \mathrm{B}_2 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{Low Development}_{st} + \mathrm{B}_3 \log(\text{Household Income per Capita}_{\mathrm{i\,t}}) \times \text{High Development}_{st} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t}} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t}} \times \text{Low Development}_{st} + \mathrm{B}_4 \text{ Relative Income}_{\mathrm{i\,t}} \times \text{High Development}_{st} + B_j X_{it} + \mathrm{Z_i}\gamma + \mathrm{A_i} + \mathrm{U}_{\mathrm{i\,t}}$$

We used the Hausmann test to select our panel data models specifications. All models were specified in two stages, first at the lowest level (individual and household factors only), followed by a specification in which the municipal factors are added.

Models 1 to 3 were flawed as they failed to parse out the random effects that occur at the municipal level. This was due to their inability to account for the clustered nature of our data structure. Such models measure the total within sample effect amongst all observations. To confirm whether municipal development context altered the contribution of absolute and relative income to life satisfaction ratings, we isolated the influence of municipal factors through a multilevel model.

Multilevel models (MLMS) are also referred to as hierarchical or random-effects models. These models are used to interrogate the relationship between explanatory variables clustered in higher-level groups and a dependent variable at the lowest level of analysis. In the present case, we were interested in the effect of municipal, household, and individual effects on individual-level SWB. Multilevel models are designed to take account of this nested data structure. This is done by decomposing the error term into various components arising from unobserved effects at different levels, and then estimating their variance to enable the calculation of standard errors. This partitioning of the random effect controls for the unobservable effects of groups within which observations are nested. This contrasts with conventional linear regression in which nesting goes unaccounted by assuming the entire random effect occurs at only a single level. Conducting regression analysis utilizing an MLM yields regression analysis which estimates both a fixed part and a random part. The fixed part of the model estimates the influence of observed explanatory variables at all levels, while the random part which decomposes the error term by level of origin and estimates the variance of these components. Multilevel models are specified in two main variants: random intercept or random slopes (or coefficients).

The Random Intercept Model

$$4)\ \ SWB_{ij} = B_{0j} + B_1 X_{ij} + U_{ij}$$

Where B_{0j} *= average intercept γ00 plus group-dependent deviation*

$$5)\ \ U_{0j}: B_{0J} = \gamma_{OO} + R_{ij}$$

In this model, the regression coefficient B_1 *is common to all the groups.*

The simplest form of MLM is that in which the model is specified without accounting for random effects originating at different levels. This is known as the “fixed intercept model” in which individuals are not clustered into municipalities resulting in a single level model analogous to the ordinary least squares (OLS) linear regression. In the fixed intercept model, the mean outcome between groups is restricted from varying as R_{ij} is assumed to be zero, forcing $B_{0J} = \gamma_{OO}$ (Snijders & Bosker, 2011). The fixed coefficient estimates generated by this model are similar to those of linear regression. However, there tends to be an underestimation of the standard errors, which negatively impacts inference testing. Instead, we employed the random intercept model because our analysis focused on how individual life satisfaction ratings vary between municipalities. This first model specification does not assume the value of R_{ij} effectively resulting in $B_{0J} \neq \gamma_{OO}$. This yields the “random intercepts” model in which each group’s intercept is allowed to vary by some random factor from the grand mean, introducing random effects into our analysis. It is assumed that the random components are normally distributed, have a mean value of zero conditional on the explanatory variables and constant variance. Such a model accounts for the fact that the average effect of the explanatory variables will be similar amongst individuals in the same municipality as opposed to those in differing municipalities. Different socio-economic contexts as expressed through the explanatory variables in each municipality will lead to higher or lower effects on SWB given the municipality.

The Random slope/coefficient model.

$$6)\quad SWB_{ij} = B_{oj} + B_{ij}X_{ij} + R_{ij}$$
$$7)\quad B_{0j} = \gamma_{00} + U_{0j}$$
$$8)\quad B_{1j} = \gamma_{10} + U_{1j}$$

Substitution of 6) and 7) into 5) yields:

$$9)\quad SWB_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + U_{0j} + U_{1j}X_{ij} + R_{ij}$$

The random slope/coefficient model introduces a further alteration which enables the modelling of within-group variation. This model acknowledges differences in rates of change between groups owing to systematic variance of correlates in different municipalities. While a strict random slope model implies independence of the slope from each group it enforces the same average on all groups implying that all groups have the same starting point. An improvement on both specifications is a hybrid model incorporating both random intercepts and random slopes. This model allows for independence in the overall average and rate of change amongst groups allowing for maximum variation. In this way, this model captures both within-group effects and between-group effects absorbing more information from the data.

The random intercept model works with the assumption that the relationship between the x variables and our dependent variable is identical between groups. This is an excessively limiting assumption to adhere to without a priori theoretical validation. A model in which within-group variation is allowed permits more variation and thereby richer analysis. Such a model is the random slope model which allows both the intercept and slope to vary and our interest is the slope. This model decomposes both the intercept slope coefficient of each group into a fixed and random component as illustrated by equations 7) and 8). This can be interpreted as there being a general slope across all municipalities, however, each municipality's slope coefficient is allowed to vary from this slope by some random slope component unique to each group. A similar interpretation applies to the intercept as encountered in the random intercept model. In municipalities whose random slope coefficient is positive (negative) the fixed slope will have a steeper (flatter) slope than average.

The Likelihood Ratio (LR) test is used to select between the various MLM models presented in this section. The LR test compares nested models where the base model is a deprecated model nested within an overspecified model. This test allows us to compare the statistical significance of specifying our models with more levels. Once the choice between random intercepts and slopes has been made, we then test for the significance of fixed effects using the LR test where the base model omits the explanatory variables. We report the results of our LR tests in the Appendix (See Appendix – Table 11). We also include the Intraclass Correlation Coefficient (ICC) (See Appendix – Table 11) which measures the degree to which observations in each group are similar to one another other. The motivation for MLM is that observations within each group have more in common than they do with observations from other groups. The ICC is used to provide evidence for this reporting values greater than zero as the similarity between observations in a group increase.

Principal Component Analysis

We employed Principal Component Analysis (PCA) as a method of dimensionality reduction. We began by ensuring that all variables were expressed in the same direction of correlation with SWB. Variables which were positively correlated with SWB were left untouched. On the other hand, variables which were negatively correlated with SWB are transformed into the inverse such that their correlation became positive. This yielded principal components which were positively correlated with socioeconomic factors which increase SWB. This ensured a simple interpretation of principal components as indicators of positive socioeconomic development from the viewpoint of SWB. Higher values of the principal component were taken to indicate a higher level of socioeconomic development, and lower factors interpreted likewise. The principal component generated is built as an interval scale such that its range lacks a zero lower-bound, allowing for negative socio-economic development to be tracked. Negative numbers were interpreted as representing municipalities that have experienced decay in overall socio-economic development. Categorization of municipalities into development groups was conducted by implementing symmetric cut-offs at various points of the generated socioeconomic index's distribution. These points were at the top and bottom 10%, 25% and 50% of the Principal component's distribution, allowing socioeconomic development classification to vary from extreme to moderate respectively.

Principal component analysis reduces dimensionality by summarizing many variables into a single factor. "This means that 'preserving as much variability as possible' translates into finding new variables that are linear functions of those in the original dataset, that successively maximize variance and that are uncorrelated with each other. Finding such new variables, the principal components (PCs), reduces to solving an eigenvalue/eigenvector problem."(Jolliffe & Cadima, 2016). As a variance maximization technique, this technique is sensitive to scale differences between variables which may over/understate the variance within a particular variable. As such, it is recommended that variables are scaled such that PCA is conducted with a correlation matrix instead of a covariance matrix. PCA solves an equation in which the correlation matrix is differenced from the eigenvalue and this entire equation is multiplied by the eigenvalue

$$10)\ (R - \lambda I)\, \mu = 0.$$

We employed Kaiser's rule with factor selection which dictates that only Principal Components with eigenvalues exceeding 1 should be retained. For our current variables, we obtained two-factor components with eigenvalues greater than 1(see Appendix Table 2, 3, and figure 4). We opted to retain the factor with the highest eigenvalue for our analysis as this explains a high degree of variation of 47% (see Appendix Table 2). This decision foregoes the need to re-orient the factors such that loading is maximized on only a few variables. This would allow for the labelling of factors according to the variables on which they are heavily loaded. Since we only retained a single factor there are no other factors for comparison and, so our lone factor is the socioeconomic index by default, given its composition of socioeconomic variables. Finally, the Kaiser-Meyer-Olkin measure of sampling adequacy was reported at 0.5156 indicating our underlying municipal variables have 51% of variance in common (see Appendix-Table 5). As this is above 0.5, this indicates our dataset warranted dimensionality reduction.

Results

Our regressions are conducted over two stages: the first stage entails running regression without municipal contextual variables and in the second stage we conduct regressions including municipal context. This was done to establish a baseline for comparison. Based on the results from our Hausman test which reported a p-value less than 0,05 we rejected the null hypothesis that the random-effects model is the preferred model. As such, we omitted the panel data random effects regression results. We ran a two-level model with level one comprising individual and household factors, while level two comprised municipal level factors as accounted for by our socioeconomic development index. Only the fixed effects of our MLM models were presented, with the random effects reported in the Appendix (see Appendix-Tables 8, 9 and 10). All regressions presented in the proceeding tables are unweighted.

Regressions without municipal context

We begin with a look at the results from Table 2. These regressions were run without municipal development context. Absolute income effects were found to be large and highly significant across all models. Relative income effects contributed to a larger effect than absolute income effects. Education was found to have a positive increasing effect. Obtaining a matric certificate led to higher SWB than having no education and obtaining a university degree led to even greater SWB effects. Age, being male, being black and unemployment each contributed a very small effect to SWB, which was found to be significant. Religion and marriage contributed large and statistically significant effects on SWB. SWB was found to be increasing although at a very small rate as a function of time and formal housing.

Table 2:Regressions without municipal developmental context

VARIABLES	OLS	FE	MLM

Absolute Income			
Household Income per Capita	0.180***	0.185***	0.183***
	(0.011)	(0.011)	(0.011)
Relative Income	0.353***	0.354***	0.356***
	(0.012)	(0.012)	(0.012)
Education Level			
1.Matric Certificate	0.208***	0.223***	0.220***
	(0.033)	(0.033)	(0.033)
2.University Degree	0.333***	0.394***	0.393***
	(0.060)	(0.060)	(0.060)
Age	-0.050***	-0.055***	-0.055***
	(0.006)	(0.006)	(0.006)
Age squared	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Black	-1.085***	-0.829***	-0.829***
	(0.027)	(0.038)	(0.038)
Unemployed	-0.131***	-0.122***	-0.119***
	(0.026)	(0.026)	(0.026)
Religion	0.504***	0.447***	0.452***
	(0.038)	(0.038)	(0.038)
Healthy	0.499***	0.512***	0.512***
	(0.077)	(0.076)	(0.076)
Married	0.292***	0.315***	0.313***
	(0.027)	(0.027)	(0.027)
Male	-0.027	-0.049**	-0.047**
	(0.022)	(0.022)	(0.022)
Formal Housing	0.245***	0.212***	0.214***
	(0.027)	(0.027)	(0.027)
Wave Dummy			
Wave 2	-0.609***	-0.593***	-0.594***
	(0.039)	(0.039)	(0.040)
Wave 3	-0.484***	-0.472***	-0.481***
	(0.037)	(0.037)	(0.039)
Wave 4	-0.051	-0.028	-0.030
	(0.036)	(0.036)	(0.042)
Wave 5	-0.102***	-0.067*	-0.061
	(0.037)	(0.036)	(0.050)
Constant	4.111***	4.018***	4.216***
	(0.164)	(0.165)	(0.220)
Observations	44,520	44,487	44,487
R-squared	0.134	0.100	
Number of dc2011		52	
Number of groups			52

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regressions with municipal context

Table 4 displays our results from regressions run with municipal context. Absolute income, in general, exhibited large and significant effects on SWB as in the previous table. Once context was added, the OLS estimates diverged from those of the FE and MLM models. The OLS model found absolute income effects to be extremely small regardless of context, however only significant in high development contexts. The FE and MLM reported small and significant absolute income effects in high development contexts. The FE model found larger, insignificant absolute income effects in low development contexts. This was echoed by the MLM with the exception that absolute income effects were found to be significant.

Relative income effects for the general case exhibited similar characteristics as found in the previous table. Across all models estimates in either development context exhibited similar characteristics. Relative income was found to exert a very small and insignificant effect in highly developed municipalities. In highly developed contexts, relative income effects were found to be large and significant.

We conducted robustness checks by running similar regressions at the 10th and 50th percentile cut-offs. These regressions reported similar magnitudes for the absolute and relative income effects suggesting our findings are robust. We included these regressions and their relevant statistics in the Appendix (see Appendix-Tables 7 to 11)

Table 3:Regressions with municipal developmental context

VARIABLES	OLS	FE	MLM
Absolute Income			
Household Income per Capita	0.211***	0.209***	0.198***
	(0.013)	(0.013)	(0.013)
Household Income per Capita*Low Development	-0.070***	-0.082***	-0.071***
	(0.011)	(0.013)	(0.013)
Household Income per Capita*High Development	-0.007	-0.001	0.017
	(0.011)	(0.012)	(0.013)
Relative Income	0.306***	0.296***	0.297***
	(0.018)	(0.018)	(0.018)
Relative Income *Low Development	0.181***	0.202***	0.203***
	(0.027)	(0.027)	(0.028)
Relative Income* High Development	-0.028	-0.010	-0.010
	(0.028)	(0.028)	(0.028)
Education Level			
1.Matric Certificate	0.209***	0.222***	0.219***
	(0.033)	(0.033)	(0.033)
2.University Degree	0.328***	0.390***	0.389***
	(0.060)	(0.060)	(0.060)

Age	-0.049***	-0.054***	-0.054***
	(0.006)	(0.006)	(0.006)
Age squared	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Black	-1.080***	-0.828***	-0.825***
	(0.027)	(0.038)	(0.038)
Unemployed	-0.130***	-0.121***	-0.118***
	(0.026)	(0.026)	(0.026)
Religion	0.504***	0.447***	0.453***
	(0.038)	(0.038)	(0.037)
Healthy	0.493***	0.505***	0.506***
	(0.077)	(0.076)	(0.076)
Married	0.293***	0.314***	0.311***
	(0.027)	(0.027)	(0.027)
Male	-0.026	-0.049**	-0.047**
	(0.022)	(0.022)	(0.022)
Formal Housing	0.241***	0.213***	0.216***
	(0.027)	(0.027)	(0.027)
Wave Dummy			
Wave 2	-0.604***	-0.589***	-0.589***
	(0.039)	(0.039)	(0.040)
Wave 3	-0.474***	-0.464***	-0.470***
	(0.037)	(0.037)	(0.039)
Wave 4	-0.032	-0.016	-0.019
	(0.036)	(0.037)	(0.043)
Wave 5	-0.084**	-0.062	-0.045
	(0.037)	(0.039)	(0.051)
Constant	4.048***	4.006***	4.251***
	(0.164)	(0.165)	(0.224)
Observations	44,520	44,487	44,487
R-squared	0.135	0.101	
Number of dc2011		52	
Number of groups			52
ICC			.1260908

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

The finding that absolute income effects were larger in the most highly developed 25% of municipalities as opposed to the least developed 25% is anticipated in line with the “human needs hypothesis”. Lower levels of public goods provision in the lowest developed 25% of municipalities, results in basic capability deprivation which low levels of income are incapable of rectifying. Income earned fails to meet one’s needs and as such absolute income effects are diminished. Individuals in the most developed 25% of municipalities are most likely reside in urban areas and benefit from higher pubic good provision, such that basic needs are met. Even where public good provision is lacking, individuals in these contexts can use their income to access such goods in the market. As such, absolute income effects are relatively larger.

The absolute effect of income in low development municipalities was much smaller than in highly developed contexts as well as statistically significant. We interpreted this to mean that while income is vital in this context, individuals in this context earned too little and were further constrained by the environment to maximise their use of their income. Incomes earned by individuals in such contexts may be too low to afford them much needed access to privately provided services such as housing, water, electricity, schooling and healthcare considered to be basic goods. Consumption of these goods if at all accessed comes from public provision, not personal income. As such, consumption funded by income earned was so low it only exerted a very small effect on SWB. The statistical significance of this estimate suggests that higher-income may lead to higher absolute effects once basic needs are met.

Relative income effects in the general case exerted large and significant influences on SWB. We interpreted this to mean that relative income effects were generally important across the income distribution in South Africa. When developmental context was accounted for, we found there to be large and significant relative income effects in the lowest developed 25% of municipalities. This was in contrast to the small and insignificant contrast effects found in the most developed 25% of municipalities. These findings were consistent with estimates for similar models analysed at the 10th and 50th percentile cut-offs. Regardless of the choice of developmental category definition, our models indicate larger absolute effects for individuals in the most developed municipalities and larger relative income effects for individuals in the least developed municipalities.

This may be explained by much narrower reference group formation in poorer municipalities than in rich ones. This would result in limited information sets which insulate individuals from comparisons with individuals with vastly different life circumstances. The smaller relative effects in the most developed 25% of municipalities may be caused by increased competition in one's environment which raises stress experienced by individuals. Increased competition amongst individuals may also result in longer working hours needed to attain an income advantage over one's references group. Wu and Tam (2011) found that relative effects don't explain much of the variation between income and SWB. This study reports contradictory results. Contrast effects in only the highly developed context tended to be small and insignificant.

Our overall findings illustrate a different narrative than that proposed in the Easterlin Paradox. SWB grows as income increases however, this is driven by a dominance of absolute effects rather than relative effects as Easterlin proposed (Easterlin, 1974). Relative income effects loom large for the low development municipalities of the distribution only because their sphere of reference is limited to their most immediate neighbours (Kingdon & Knight, 2007; Posel & Casale, 2011). The same phenomenon of limiting spheres of reference is observed in the richest 25% of municipalities driving low relative effects as observed in Wu & Tam (2015)'s Chinese study. In conjunction, these observations point to the highly divisive nature of South African society. Emerging from this study's findings is the distortions spatial inequality exerts on the income and SWB relationship,

Future research employing quantile regression methods is necessary to investigate income effect dynamics in the full range of developmental contexts. A further improvement would include race or ethnicity as a contextual variable given race's significant effect in this and other related South African studies. Klasen (2000)'s use of expenditure instead of income points to a further improvement in future research as expenditure is more closely linked with consumption.

References

Alexander, L., & Tredoux, C. (2010). The spaces between us: A spatial analysis of informal segregation at a South African university. *Journal of Social Issues*, *66*(2), 367–386.

Anderson, C., Kraus, M. W., Galinsky, A. D., & Keltner, D. (2012). The Local-Ladder Effect: Social Status and Subjective Well-Being. *Psychological Science*. https://doi.org/10.1177/0956797611434537

Bhorat, H., Stanwix, B., & Yu, D. (2014). *Non-Income Welfare And Inclusive Growth In South Africa* [Working Paper]. University of Cape Town, Development Policy Research Unit. https://econpapers.repec.org/paper/ctwwpaper/201407.htm

Birdsall, N., Ross, D., & Sabot, R. (1995). Inequality and Growth Reconsidered: Lessons from East Asia. *The World Bank Economic Review*, *9*(3), 477–508. https://doi.org/10.1093/wber/9.3.477

Blaauw, D., & Pretorius, A. (2013, April 1). *The determinants of subjective well-being in South Africa—An exploratory enquiry* [Text]. Sabinet. https://www.ingentaconnect.com/content/sabinet/jefs/2013/00000006/00000001/art00011

Blanchflower, D. G., & Oswald, A. J. (2004a). Money, Sex and Happiness: An Empirical Study. *The Scandinavian Journal of Economics*, *106*(3), 393–415. https://doi.org/10.1111/j.0347-0520.2004.00369.x

Blanchflower, D. G., & Oswald, A. J. (2004b). Well-being over time in Britain and the USA. *Journal of Public Economics*, *88*(7), 1359–1386. https://doi.org/10.1016/S0047-2727(02)00168-8

Bookwalter, J. T., & Dalenberg, D. R. (2010). Relative to what or whom? The importance of norms and relative standing to well-being in South Africa. *World Development*, *38*(3), 345–355.

Brickman, P., & Campbell, D. T. (1971). *Hedonic relativism and planning the good society*.

Bukenya, J. O., Gebremedhin, T. G., & Schaeffer, P. V. (2003). Analysis of Rural Quality of Life and Health: A Spatial Approach. *Economic Development Quarterly*, *17*(3), 280–293. https://doi.org/10.1177/0891242403255325

Burns, J., Keswell, M., & Leibbrandt, M. (2005). Social assistance, gender, and the aged in South Africa. *Feminist Economics*, *11*(2), 103–115. https://doi.org/10.1080/13545700500115944

Clark, A. E. (2003). Unemployment as a Social Norm: Psychological Evidence from Panel Data. *Journal of Labor Economics*, *21*(2), 323–351. https://doi.org/10.1086/345560

Clark, A. E. (2016). Adaptation and the easterlin paradox. In *Advances in happiness research* (pp. 75–94). Springer.

Clark, A. E., & Oswald, A. J. (1994). Unhappiness and Unemployment. *The Economic Journal*, *104*(424), 648–659. JSTOR. https://doi.org/10.2307/2234639

Cohen, A. B. (2002). The Importance of Spirituality in Well-Being for Jews and Christians. *Journal of Happiness Studies*, *3*(3), 287–310. https://doi.org/10.1023/A:1020656823365

Cole, M. J., Bailey, R. M., Cullis, J. D. S., & New, M. G. (2018). Spatial inequality in water access and water use in South Africa. *Water Policy*, *20*(1), 37–52. https://doi.org/10.2166/wp.2017.111

Cramm, J. M., Møller, V., & Nieboer, A. P. (2010). Improving Subjective Well-being of the Poor in the Eastern Cape. *Journal of Health Psychology*, *15*(7), 1012–1019. https://doi.org/10.1177/1359105310367833

Davey, G., Chen, Z., & Lau, A. (2009). 'Peace in a Thatched Hut—that is Happiness': Subjective Wellbeing Among Peasants in Rural China. *Journal of Happiness Studies*, *10*(2), 239–252. https://doi.org/10.1007/s10902-007-9078-x

Diener, E., & Biswas-Diener, R. (2002). Will Money Increase Subjective Well-Being? *Social Indicators Research*, *57*(2), 119–169. https://doi.org/10.1023/A:1014411319119

Diener, E. D., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75.

Diener, E., & Lucas, R. E. (2000). Explaining Differences in Societal Levels of Happiness: Relative Standards, Need Fulfillment, Culture, and Evaluation Theory. *Journal of Happiness Studies*, *1*(1), 41–78. https://doi.org/10.1023/A:1010076127199

Diener, E., Sandvik, E., Pavot, W., & Fujita, F. (1992). Extraversion and subjective well-being in a U.S. national probability sample. *Journal of Research in Personality*, *26*(3), 205–215. https://doi.org/10.1016/0092-6566(92)90039-7

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276.

Duesenberry, J. S. (1949). *Income, saving, and the theory of consumer behavior*.

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. In *Nations and households in economic growth* (pp. 89–125). Elsevier.

Eastwood, R., & Lipton, M. (2004). Rural and urban income inequality and poverty: Does convergence between sectors offset divergence within them? In G. A. Cornia (Ed.), *Inequality, growth and poverty in an era of liberalization and globalization* (pp. 112–141). Oxford University Press. http://sro.sussex.ac.uk/id/eprint/26714/

Ebrahim, A., Botha, F., & Snowball, J. (2013). Determinants of life satisfaction among race groups in South Africa. *Development Southern Africa*, *30*(2), 168–185. https://doi.org/10.1080/0376835X.2013.797227

Emmons, R. A., & Diener, E. (1985). Personality Correlates of Subjective Well-Being. *Personality and Social Psychology Bulletin*, *11*(1), 89–97. https://doi.org/10.1177/0146167285111008

Ferrer-i-Carbonell, A. (2005). Income and well-being: An empirical analysis of the comparison income effect. *Journal of Public Economics*, *89*(5–6), 997–1019.

Ferrer-i-Carbonell, A., & Frijters, P. (2004). How Important is Methodology for the estimates of the determinants of Happiness?*. *The Economic Journal*, *114*(497), 641–659. https://doi.org/10.1111/j.1468-0297.2004.00235.x

Ferrer-i-Carbonell, A., & Gowdy, J. M. (2007). Environmental degradation and happiness. *Ecological Economics*, *60*(3), 509–516. https://doi.org/10.1016/j.ecolecon.2005.12.005

Ferriss, A. L. (2002). Religion and the Quality of Life. *Journal of Happiness Studies*, *3*(3), 199–215. https://doi.org/10.1023/A:1020684404438

Fiegehen, G. C., & Lansley, P. S. (1976). The Measurement of Poverty: A Note on Household Size and Income Units. *Journal of the Royal Statistical Society: Series A (General)*, *139*(4), 508–518. https://doi.org/10.2307/2344353

Francis, D., & Webster, E. (2019). Poverty and inequality in South Africa: Critical reflections. *Development Southern Africa*, *36*(6), 788–802. https://doi.org/10.1080/0376835X.2019.1666703

Frey, B. S., & Stutzer, A. (2000). Happiness, Economy and Institutions. *The Economic Journal*, *110*(466), 918–938. https://doi.org/10.1111/1468-0297.00570

Frey, B. S., & Stutzer, A. (2002). What Can Economists Learn from Happiness Research? *Journal of Economic Literature*, *40*(2), 402–435. https://doi.org/10.1257/002205102320161320

Gerdtham, U.-G., & Johannesson, M. (1997). *The Relationship between Happiness, Health and Socio-economic Factors: Results Based on Swedish Micro Data* (SSE/EFI Working Paper Series in Economics and Finance No. 207). Stockholm School of Economics. https://econpapers.repec.org/paper/hhshastef/0207.htm

Gimpel, J. G., & Karnes, K. A. (2006). The Rural Side of the Urban-Rural Gap. *PS: Political Science and Politics*, *39*(3), 467–472. JSTOR.

Greenberg, E. S. (1981). Industrial Self-Management and Political Attitudes. *American Political Science Review*, *75*(1), 29–42. https://doi.org/10.2307/1962157

GRIFFIN, D., & Gonzalez, R. (2013). THE ENDOWMENT—CONTRAST MODEL! A LENS FOR HAPPINESS RESEARCH. In *Oxford Handbook of Happiness* (p. 35). Oxford University Press.

Groot, W., & Maassen van den Brink, H. (2000). Life-Satisfaction and Preference Drift. *Social Indicators Research*, *50*(3), 315–328. https://doi.org/10.1023/A:1007085500976

Helliwell, J. (2001). Social Capital, the Economy and Well-being. In *The Review of Economic Performance and Social Progress* (Vol. 1). Centre for the Study of Living Standards & The Institutute for Research on Public Policy. https://ideas.repec.org/h/sls/repsls/v1y2001jh.html

Helliwell, J. F. (2003). How's life? Combining individual and national variables to explain subjective well-being. *Economic Modelling*, *20*(2), 331–360. https://doi.org/10.1016/S0264-9993(02)00057-3

Helliwell, J. F. (2006). Well-Being, Social Capital and Public Policy: What's New?*. *The Economic Journal*, *116*(510), C34–C45. https://doi.org/10.1111/j.1468-0297.2006.01074.x

Hongbin, L., & Yi, Z. (2006). Income, income inequality, and health: Evidence from China. *J Comp Econ*, *34*, 668–93.

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Kaus, W. (2013). Conspicuous consumption and "race": Evidence from South Africa. *Journal of Development Economics*, *100*(1), 63–73. https://doi.org/10.1016/j.jdeveco.2012.07.004

Kingdon, G. G., & Knight, J. (2007). Community, comparisons and subjective well-being in a divided society. *Journal of Economic Behavior & Organization*, *64*(1), 69–90. https://doi.org/10.1016/j.jebo.2007.03.004

Klasen, S. (2000). Measuring Poverty and Deprivation in South Africa. *Review of Income and Wealth*, *46*(1), 33–58. https://doi.org/10.1111/j.1475-4991.2000.tb00390.x

Knight, J., & Gunatilaka, R. (2010). The Rural–Urban Divide in China: Income but Not Happiness? *The Journal of Development Studies*, *46*(3), 506–534. https://doi.org/10.1080/00220380903012763

Kollamparambil, U. (2019). Happiness, Happiness Inequality and Income Dynamics in South Africa. *Journal of Happiness Studies*, 1–22.

Lane, R. E. (2000). Diminishing Returns to Income, Companionship – and Happiness. *Journal of Happiness Studies*, *1*(1), 103–119. https://doi.org/10.1023/A:1010080228107

Larsen, R. J., Diener, E. D., & Emmons, R. A. (1985). An evaluation of subjective well-being measures. *Social Indicators Research*, *17*(1), 1–17.

Leibbrandt, M., Finn, A., & Woolard, I. (2012). Describing and decomposing post-apartheid income inequality in South Africa. *Development Southern Africa*, *29*(1), 19–34. https://doi.org/10.1080/0376835X.2012.645639

Lester, A., Nel, E., & Binns, T. (2000). *South Africa, Past, Present and Future*. Prentice Hall. http://www.amazon.co.uk/South-Africa-Past-Present-Future/dp/0582356261#reader_0582356261

Lilenstein, K., Woolard, I., & Leibbrandt, M. (2018). In-work poverty in South Africa: The impact of income sharing in the presence of high unemployment. *Handbook on In-Work Poverty*. https://www.elgaronline.com/view/edcoll/9781784715625/9781784715625.00032.xml

McLennan, D., Noble, M., & Wright, G. (2016). Developing a spatial measure of exposure to socio-economic inequality in South Africa. *South African Geographical Journal*, *98*(2), 254–274. https://doi.org/10.1080/03736245.2015.1028980

Mentzakis, E., & Moro, M. (2009). The poor, the rich and the happy: Exploring the link between income and subjective well-being. *The Journal of Socio-Economics*, *38*(1), 147–158. https://doi.org/10.1016/j.socec.2008.07.010

Mojtabai, R., Olfson, M., & Han, B. (2016). National Trends in the Prevalence and Treatment of Depression in Adolescents and Young Adults. *Pediatrics*, *138*(6). https://doi.org/10.1542/peds.2016-1878

Myers, D. G., & Diener, E. (1996). The Pursuit of Happiness. *Scientific American*, *274*(5), 70–72. JSTOR.

Noble, M., & Wright, G. (2013). Using Indicators of Multiple Deprivation to Demonstrate the Spatial Legacy of Apartheid in South Africa. *Social Indicators Research*, *112*(1), 187–201. https://doi.org/10.1007/s11205-012-0047-3

Pattie, C., & Johnston, R. (2011). How Big is the Big Society? *Parliamentary Affairs*, *64*(3), 403–424. https://doi.org/10.1093/pa/gsr013

Pholphirul, P. (2014). Healthier and Happier? The Urban-Rural Divide in Thailand. *Journal of Human Behavior in the Social Environment*, *24*(8), 973–985. https://doi.org/10.1080/10911359.2014.945064

Posel, D. R., & Casale, D. M. (2011). Relative standing and subjective well-being in South Africa: The role of perceptions, expectations and income mobility. *Social Indicators Research*, *104*(2), 195–223.

Powdthavee, N. (2005). Unhappiness and Crime: Evidence from South Africa. *Economica*, *72*(287), 531–547. https://doi.org/10.1111/j.0013-0427.2005.00429.x

Ray, D. (2010). Uneven Growth: A Framework for Research in Development Economics. *Journal of Economic Perspectives*, *24*(3), 45–60. https://doi.org/10.1257/jep.24.3.45

Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. SAGE.

Sørensen, J. F. L. (2014). Rural–Urban Differences in Life Satisfaction: Evidence from the European Union. *Regional Studies*, *48*(9), 1451–1466. https://doi.org/10.1080/00343404.2012.753142

Steptoe, A., Deaton, A., & Stone, A. A. (2015). Subjective wellbeing, health, and ageing. *The Lancet*, *385*(9968), 640–648. https://doi.org/10.1016/S0140-6736(13)61489-0

Stevenson, B., & Wolfers, J. (2008). *Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox* (Working Paper No. 14282; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w14282

Tella, R. D., MacCulloch, R. J., & Oswald, A. J. (2003). The Macroeconomics of Happiness. *The Review of Economics and Statistics*, *85*(4), 809–827. https://doi.org/10.1162/003465303772815745

van Praag, B. M. S., Frijters, P., & Ferrer-i-Carbonell, A. (2003). The anatomy of subjective well-being. *Journal of Economic Behavior & Organization*, *51*(1), 29–49. https://doi.org/10.1016/S0167-2681(02)00140-3

Wang, H., Cheng, Z., & Smyth, R. (2019). Consumption and Happiness. *The Journal of Development Studies*, *55*(1), 120–136. https://doi.org/10.1080/00220388.2017.1371294

Warshaw, M. G., Klerman, G. L., & Lavori, P. W. (1991). Are secular trends in major depression an artifact of recall? *Journal of Psychiatric Research*, *25*(3), 141–151. https://doi.org/10.1016/0022-3956(91)90007-W

Wei, M., Shaffer, P. A., Young, S. K., & Zakalik, R. A. (2005). Adult Attachment, Shame, Depression, and Loneliness: The Mediation Role of Basic Psychological Needs Satisfaction. *Journal of Counseling Psychology*, *52*(4), 591–601. https://doi.org/10.1037/0022-0167.52.4.591

Welsch, H. (2002). Preferences over Prosperity and Pollution: Environmental Valuation based on Happiness Surveys. *Kyklos*, *55*(4), 473–494. https://doi.org/10.1111/1467-6435.00198

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological Economics*, *58*(4), 801–813. https://doi.org/10.1016/j.ecolecon.2005.09.006

White, H., & Masset, E. (2003). The Importance of Household Size and Composition in Constructing Poverty Profiles: An Illustration from Vietnam. *Development and Change*, *34*(1), 105–126. https://doi.org/10.1111/1467-7660.00298

Wu, H. F., & Tam, T. (2015). Economic development and socioeconomic inequality of well-being: A cross-sectional time-series analysis of urban China, 2003–2011. *Social Indicators Research*, *124*(2), 401–425.

Appendix

Appendix – Table1: Table of variable definitions

Variable	Type	Definition
Individual and Household Level Variables		
Satisfaction	Categorical	Satisfaction with life rating (equivalent to SWB)
Household Income per Capita	Continuous	Logarithm of Household income divided by the number of household residents
Relative income	Categorical	Perceived income status relative to surrounding community members
Education Level	Categorical	Highest education level achieved
Age	Continuous	Respondent's age in years
Black	Dummy	If racial category is Black = 1, otherwise = 0
Unemployed	Dummy	If unemployed = 1, otherwise = 0
Religion	Dummy	If religion is practiced = 1, otherwise 0
Healthy	Dummy	If respondent is healthy = 1, otherwise = 0
Married	Dummy	If respondent is married = 1, otherwise = 0
Male	Dummy	If respondent sex is male = 1, otherwise = 0
Formal Housing	Dummy	If respondent resides in formal housing = 1, otherwise = 0
Wave	Categorical	Data collection waves to which data corresponds ranging from 2008 = 0 to 2017 = 4
District Municipality Level Variables		
Gini Coefficient	Continuous	District Municipality Gini Coefficient
Average Household income (Rand)	Continuous	District Municipality Average Household income
GRP (Gross Regional Product)	Continuous	District Municipality Gross Regional Product
Population	Continuous	District Municipality Population
Unemployment Level	Continuous	District Municipality Unemployment (Percentage)
Average Dependency Ratio	Continuous	District Municipality Average Dependency Ratio
Crime	Continuous	District Municipality Reported Murder Cases
Water	Continuous	Number of Households with Water Access/Municipal Population per District Municipality
Food Poverty line	Continuous	Number of Households below the Food Poverty Line per District Municipality
ln (GRP)	Continuous	Logarithm of Gross Regional Product per District Municipality

Appendix– Table2: Principal components/correlation

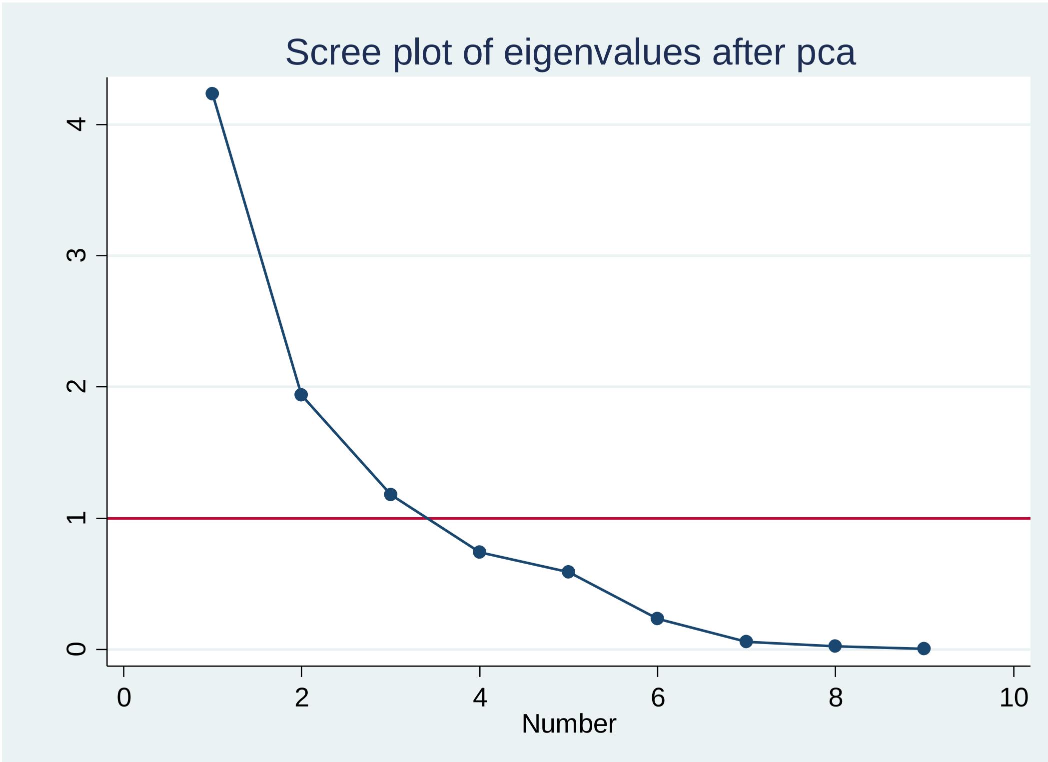
	Number of obs	=	34,527
	Number of comp.		9
	Trace		9
Rotation: (unrotated = principal)	Rho		1

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.23146	2.29479	0.4702	0.4702
Comp2	1.93667	0.756299	0.2152	0.6853
Comp3	1.18037	0.438202	0.1312	0.8165
Comp4	0.742172	0.151648	0.0825	0.899
Comp5	0.590524	0.357605	0.0656	0.9646
Comp6	0.23292	0.175442	0.0259	0.9905
Comp7	0.0574771	0.0356152	0.0064	0.9968
Comp8	0.0218619	0.0153276	0.0024	0.9993
Comp9	0.0065343	.	0.0007	1

Appendix– Table3: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Unexp
Average Household income (Rand)	0.4648	-0.0475	0.0532	-0.1911	0.0451	0.3417	-0.566	0.3735	-0.4052	0
ln (GRP)	0.4794	-0.0349	-0.0228	-0.0338	0.1169	-0.0515	0.1609	-0.7584	-0.3871	0
Population	0.4708	-0.0508	-0.1819	-0.1078	-0.032	-0.0005	-0.267	-0.1577	0.7962	0
Gini Coefficient(inverse)	0.2712	0.2171	0.4228	0.6678	0.1127	-0.445	-0.168	0.1243	0.013	0
Average Dependency Ratio(inverse)	0.3016	0.43	-0.1223	-0.4716	0.1863	-0.4284	0.3771	0.3533	-0.0391	0
Unemployment Level(inverse)	0.0237	0.6453	-0.0744	0.2527	0.2681	0.6317	0.1728	-0.0423	0.1051	0
Crime(inverse)	0.3452	-0.1038	-0.3289	0.3433	-0.646	0.1167	0.3852	0.2373	-0.0893	0
Food Poverty line(inverse)	0.19	-0.2537	0.7511	-0.1877	-0.028	0.2894	0.4196	0.093	0.1758	0
Water	0.1099	-0.52	-0.3033	0.2557	0.6674	0.0518	0.2413	0.2311	0.0208	0

Appendix:– Table4: PCA Scree plot



Appendix– Table5: Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
Average Household income (Rand)	0.6189
ln (GRP)	0.6719
Population	0.59
Gini Coefficient(inverse)	0.6501
Average Dependency Ratio(inverse)	0.483
Unemployment Level(inverse)	0.2965
Crime(inverse)	0.5357
Food Poverty line(inverse)	0.251
Water	0.262
Overall	0.5156

Appendix– Table6: Regression with municipal development context- 10th percentile cut-off

VARIABLES	OLS	FE	RE	MLM
Absolute Income				
Household Income per Capita	0.193***	0.189***	0.189***	0.176***
	(0.011)	(0.012)	(0.012)	(0.012)
Household Income per Capita*Low Development	-0.074***	-0.091***	-0.087***	-0.077***
	(0.015)	(0.017)	(0.017)	(0.018)
Household Income per Capita * High Development	-0.015	0.034*	0.023	0.109***
	(0.014)	(0.018)	(0.017)	(0.022)
Relative Income	0.343***	0.342***	0.342***	0.343***
	(0.013)	(0.013)	(0.013)	(0.013)
Relative Income *Low Development	0.152***	0.164***	0.163***	0.169***
	(0.039)	(0.039)	(0.039)	(0.039)
Relative Income* High Development	-0.050	-0.020	-0.025	-0.010
	(0.036)	(0.037)	(0.036)	(0.037)
Education Level				
1.Matric Certificate	0.204***	0.221***	0.219***	0.219***
	(0.033)	(0.033)	(0.033)	(0.033)
2.University Degree	0.330***	0.392***	0.385***	0.388***
	(0.060)	(0.060)	(0.060)	(0.060)
Age	-0.050***	-0.055***	-0.054***	-0.055***
	(0.006)	(0.006)	(0.006)	(0.006)
Age squared	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-1.099***	-0.827***	-0.861***	-0.820***
	(0.027)	(0.038)	(0.037)	(0.038)
Unemployed	-0.135***	-0.122***	-0.124***	-0.119***
	(0.026)	(0.026)	(0.026)	(0.026)
Religion	0.496***	0.445***	0.450***	0.452***
	(0.038)	(0.038)	(0.038)	(0.038)
Healthy	0.491***	0.510***	0.507***	0.511***
	(0.077)	(0.076)	(0.076)	(0.076)
Married	0.292***	0.314***	0.312***	0.310***
	(0.027)	(0.027)	(0.027)	(0.027)
Male	-0.029	-0.050**	-0.048**	-0.047**
	(0.022)	(0.022)	(0.022)	(0.022)
Formal Housing	0.236***	0.213***	0.215***	0.213***
	(0.027)	(0.027)	(0.027)	(0.027)
Wave Dummy				
Wave 2	-0.609***	-0.595***	-0.595***	-0.592***
	(0.039)	(0.039)	(0.039)	(0.040)
Wave 3	-0.485***	-0.479***	-0.479***	-0.480***
	(0.037)	(0.037)	(0.037)	(0.040)
Wave 4	-0.057	-0.045	-0.044	-0.020
	(0.036)	(0.037)	(0.037)	(0.045)

Wave 5	-0.098***	-0.095**	-0.090**	-0.066
	(0.037)	(0.038)	(0.038)	(0.054)
Constant	4.132***	4.028***	4.079***	4.315***
	(0.164)	(0.165)	(0.170)	(0.237)
Observations	44,520	44,487	44,487	44,487
R-squared	0.135	0.101		
Number of dc2011		52	52	
Number of groups				52
ICC				.1665284

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix – Table7: Regressions with municipal development context-50th percentile cut-off

VARIABLES	OLS	FE	RE	MLM
Absolute Income				
Household Income per Capita	0.208***	0.212***	0.211***	0.211***
	(0.012)	(0.012)	(0.012)	(0.012)
Household Income per Capita*Low Development	-0.051***	-0.058***	-0.056***	-0.056***
	(0.009)	(0.011)	(0.011)	(0.011)
Relative Income	0.277***	0.273***	0.273***	0.273***
	(0.016)	(0.016)	(0.016)	(0.016)
Relative Income *Low Development	0.163***	0.174***	0.173***	0.173***
	(0.023)	(0.023)	(0.023)	(0.023)
Education Level				
1.Matric Certificate	0.207***	0.221***	0.219***	0.219***
	(0.033)	(0.033)	(0.033)	(0.033)
2.University Degree	0.328***	0.391***	0.383***	0.383***
	(0.060)	(0.060)	(0.060)	(0.060)
Age	-0.050***	-0.055***	-0.054***	-0.054***
	(0.006)	(0.006)	(0.006)	(0.006)
Age squared	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Black	-1.076***	-0.828***	-0.863***	-0.863***
	(0.027)	(0.038)	(0.037)	(0.037)
Unemployed	-0.130***	-0.120***	-0.122***	-0.122***
	(0.026)	(0.026)	(0.026)	(0.026)
Religion	0.507***	0.450***	0.455***	0.455***
	(0.038)	(0.038)	(0.038)	(0.038)
Health	0.496***	0.509***	0.506***	0.506***
	(0.077)	(0.076)	(0.076)	(0.076)
Married	0.292***	0.314***	0.311***	0.311***
	(0.027)	(0.027)	(0.027)	(0.027)
Male	-0.026	-0.049**	-0.047**	-0.047**
	(0.022)	(0.022)	(0.022)	(0.022)
Formal Housing	0.249***	0.213***	0.216***	0.216***
	(0.027)	(0.027)	(0.027)	(0.027)
Wave Dummy				
Wave 2	-0.611***	-0.594***	-0.595***	-0.595***
	(0.039)	(0.039)	(0.039)	(0.039)
Wave 3	-0.479***	-0.465***	-0.466***	-0.466***
	(0.037)	(0.037)	(0.037)	(0.037)
Wave 4	-0.038	-0.014	-0.015	-0.015
	(0.036)	(0.037)	(0.036)	(0.036)
Wave 5	-0.091**	-0.055	-0.057	-0.057
	(0.037)	(0.037)	(0.037)	(0.037)
Constant	4.061***	4.002***	4.044***	4.044***
	(0.164)	(0.165)	(0.170)	(0.170)

Observations	44,520	44,487	44,487	44,487
R-squared	0.135	0.101		
Number of dc2011		52	52	52
Number of groups				
ICC				.1271622

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix – Table8: Random effects estimates for Random Slope MLM – 10th percentile cut-offs

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
dc2011: Unstructured				
sd(pc1)	1.203232	.1551551	.9015044	1.516581
sd(_cons)	1.194166	.2050788	.8528729	1.672033
corr(pc1,_cons)	.7176674	.0798994	.5225934	.841338
sd(Residual)	2.191437	.0073631	2.177053	2.205916

Appendix – Table9: Random effects estimates for Random Slope MLM – 25th percentile cut-offs

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
dc2011: Unstructured				
sd(pc1)	1.139132	0.152907	0.875622	1.481945
sd(_cons)	1.100917	0.196412	0.776057	1.561764
corr(pc1,_cons)	0.754311	0.069496	0.582912	0.861441
sd(Residual)	2.191071	0.007361	2.17669	2.205546

Appendix – Table10: Random effects estimates for Random Slope MLM – 50th percentile cut-offs

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
dc2011: Unstructured				
sd(pc1)	1.146477	0.152593	0.883228	1.488188
sd(_cons)	1.11599	0.195984	0.791001	1.574504
corr(pc1,_cons)	0.755818	0.070031	0.582503	0.863395
sd(Residual)	2.191266	0.007362	2.176885	2.205742

Appendix – Table11: MLM statistics

10th percentile						
	Fixed Effects	Random Intercept	Random slope	RI v F	RS v RI	RS v F
Log Likelihood	-98626.518	-98268.115	-98203.674	-	-	-
Wald chi2(18)	6953.42	5068.99	4751.78	-	-	-
Prob > chi2	0	0	0	-	-	-
ICC	-	.0220526 (.0046104)	.2289553 (.0606874)	-	-	-
LR test	-	-	-	576.51***	128.88***	705.39***
25th percentile						
	Fixed Effects	Random Intercept	Random slope	RI v F	RS v RI	RS v F
Log Likelihood	-98622.799	-98247.434	-98189.403	-	-	-
Wald chi2(18)	6962.02	5118.48	4796.93	-	-	-
Prob > chi2	0	0	0	-	-	-
ICC	-	.0212636 (.0044344)	.2015727 (.0574741)	-	-	-
LR test	-	-	-	610.78***	116.06***	726.84***
50th percentile						
	Fixed Effects	Random Intercept	Random slope	RI v F	RS v RI	RS v F
Log Likelihood	-98636.908	-98253.985	-98194.051	-	-	-
Wald chi2(18)	6929.40	5104.26	4785.15	-	-	-
Prob > chi2	0	0	0	-	-	-
ICC	-	.0211766 (.0044038)	.2059562 (.0574868)	-	-	-
LR test	-	-	-	625.04***	119.87***	744.91***