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ORIGINAL RESEARCH

Estimating the Cost of Crime Victimization: A Compensating Income Variation Approach Using Different Utility Proxies

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Abstract

The relationship between subjective well-being and fear of crime is well-evidenced, but the cost of crime victimization is relatively understudied. We estimate the monetary compensation needed to offset the change from non-victim to victim of burglary or assault, using the compensating income variation method on seven waves of data from the South African Social Attitude Survey conducted in 2009, 2010, 2011, 2015, 2016, 2017, and 2018. We explore the sensitivity of results to different model specifications and utility proxies, including the first-ever utilization of the personal well-being index in compensating income variation research. Results show that models using the personal well-being index have higher predictability, but they produce considerably higher willingness-to-pay or compensating income variation estimates than those using the general life satisfaction questions and the global happiness question. We find the willingness to pay to avoid suffering the consequences of burglary or assault to range between USD 1581 and USD 4242 per year for the average-income person. However, there is large heterogeneity in willingness-to-pay across income groups. The measured value of not suffering burglary or assault along with the high prevalence of victimization in South Africa highlights the substantial financial and societal impacts of crime and the urgent need for targeted policy interventions, particularly in contexts marked by significant income disparities.

Keywords Crime victimization · Subjective well-being · Non-market valuation · Compensating income variation · Willingness to pay · Personal well-being index

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1 Introduction

> Crime, even if it has not affected us directly, is everybody's problem. If we continue to work together as government, the business community, labour and civil society, we can restore the safety and security that is critical to economic activity and the creation of jobs (*President Cyril Ramaphosa, South African Government News Agency, 5th August 2024*).

The impact of crime on individual well-being has attracted increasing attention across the globe (Baranyi et al., 2021). Crime and the fear of crime are among the most important dimensions of well-being (Sulemana, 2015; Stiglitz, Sen, and Fitoussi, 2009), and hence considered loci of well-being interventions (Lorenc et al., 2012). Previous studies in different countries and continents have found crime victimization to be negatively related to subjective wellbeing, including Janssen et al. (2021), Ortega Londoño et al. (2019), Spencer and Liu (2019), Mahuteau and Zhu (2016), Cheng and Smyth (2015). Yet, the cost of the human suffering related to crime victimization, i.e., the amount of money that an individual is willing to pay to avoid being a victim of crime, is relatively understudied, particularly outside the Western world, and heterogeneity exists across previous studies (see Table S1, supplementary materials). Of the 11 studies estimating the cost of crime victimization, only three were conducted in developing countries where crime tends to be more pronounced (Spencer & Liu, 2019; Chen and Smyth, 2015; Powdthavee, 2005).

Estimating the cost of crime victimization provides valuable information for policy makers developing and evaluating policies and interventions in the context of scarce resources (Manning et al., 2016). This cost not only includes the pecuniary losses such as money or assets stolen, medical expenses, and days-off work, but it also includes the non-pecuniary losses such as health and psychological issues, which are an integral part of our well-being (Cohen, 2020; Freeman, 1999). Calculations of the cost of specific cases of crime often only focus on pecuniary losses, while reductions in well-being are not fully accounted for (Kuroki, 2013). In this study, we measure well-being losses by estimating the willingness to pay (WTP) to avoid suffering the consequences of burglary or assault in South Africa.

Frequently used methods to estimate the WTP for a non-market good or condition, such as crime victimization, are revealed-preference and stated-preference methods (Freeman III, Herriges, and Kling, 2014). Both are subject to methodological drawbacks. Revealed-preference methods (e.g., travel cost, hedonic pricing) rely on data from observing human behaviours in real-world settings. Revealed-preference methods are limited in terms of the types of conditions for which research opportunities are available, making it unpractical for large-scale comparisons in the prioritization of resources (Groot and van den Brink, 2004). Stated-preference methods, including contingent valuation and choice modelling, are the most used valuation methods for non-market goods (Boyle, 2017), but they are costly and time consuming (Dang, 2021; Pearce et al., 2002). These methods use surveys in which respondents are asked to report their WTP for a non-market good as a whole (contingent valuation) or make choices among alternatives that are made up of different attributes of a non-market good (choice modelling) (Mariel et al., 2021). Stated-preference methods are controversial given the issues of hypothetical bias, disparity between WTP and Willingness-To-Accept (WTA), and embedding or scope problems (Hausman, 2012; Johnston et al., 2017).

A less common method for non-market valuation is the Compensating Income Variation (CIV) method, which is also sometimes referred to as the satisfaction-with-life approach

(Ásgeirsdóttir et al., 2021). The CIV method allows estimating the amount of money or the WTP to achieve different non-market goods or desiderata, for instance the avoidance of being assaulted or burglarized. It relies on the assumption that there is a statistical association between subjective well-being, a non-market good or desideratum, and income. It uses regression techniques to estimate an implied trade-off between income and the non-market good. The CIV method has two major advantages over revealed-preference and stated-preference methods. First, subjects are not required to consider hypothetical scenarios that they have never considered before or experienced (Dolan & Kahneman, 2008; Kahneman, 2009). Second, available datasets can be used, which allows for extensive results per dollar spent on the research, making it especially valuable in resource-limited contexts. This method is considered theoretically sound and has been applied to estimate the WTP for various non-market goods (see Ásgeirsdóttir et al., 2021). With respect to crime victimization, the CIV method has been used to estimate the WTP for avoiding general crime victimization in Jamaica (Spencer & Liu, 2019) and South Africa (Powdthavee, 2005), property crime in Australia (Manning et al., 2016), being a victim of one of five specific types of crimes (out-of-home theft, out-of-home robbery, home burglary, home robbery, assault or threat) in China (Cheng & Smyth, 2015), being robbed and burglarized in Japan (Kuroki, 2013), terrorism in the British Isles and France (Frey et al., 2009), being burglarized in the United States (Cohen, 2008), being burglarized, threatened violence, and a victim of car theft in the United Kingdom (Moore & Shepherd, 2006), being the victim of domestic violence in the UK (Santos, 2013), and being the victim of physical, sexual, or psychological violence in Iceland (Ásgeirsdóttir, Hardardottir, and Jonbjarnardóttir, 2023).

South Africa provides a relevant opportunity for the application of the CIV method to estimate the cost of crime victimization, given its unique socio-economic history, high crime rates, and a high level of income inequality. South Africa is considered a country of fear, with its Apartheid past and the subsequent transitions leaving deep and lasting impacts on crime and public safety (Davis, 2017). The crime levels in the country began to increase in the 1980s, before experiencing a surge in early 1990s. During this period, the police was preoccupied with repressing and controlling black resistance while leaving other types of crime undetected (Møller, 2005). Since then, the crime epidemic of South Africa has evolved alongside economic and political transitions. The legacy of Apartheid is still felt acutely in South Africa, where economic disparities and systemic inequalities contribute to the high crime rates seen today (von Holdt, 2013). The disenfranchised communities most affected by these historical injustices are also those most vulnerable to victimization, perpetuating a cycle of fear and insecurity. Despite certain progress in economic development after the Apartheid, South Africa remains one of the most unequal countries in the world, with a Gini coefficient of 0.67 in 2018 (World Bank, 2024). Unemployment rates among South Africans are persistently high, reaching 33.5% in the second quarter of 2024, with youth unemployment even more severe (World Bank, 2024). This has contributed to frustration in the society and high crime rates (Mashapha & Mukonza, 2024).

Today, few issues trigger a more simmering debate in South Africa than crime does (Manea et al., 2023). Crime has a negative impact on the daily lives of South Africans from all walks of life, threatening their rights and freedom. According to the Gallup's Global Safety Report, fear of crime among South Africans in 2023 was significantly greater than for most citizens from other countries, except Ecuador (Gallup, 2024). For many South Africans, crime is not an abstract statistic but a daily reality that influences their quality of life. Victims of burglary or assault face not only financial losses but also long-lasting psychological effects, such as anxiety and a pervasive sense of insecurity. Communities are also profoundly affected, with crime eroding trust and social cohesion

(Manea et al., 2023). Reducing crime has been considered a top national priority since the Government of South Africa adopted the National Crime Prevention Strategy in 1996 and the White Paper on Safety and Security in 1998 (Berg & Shearing, 2011). However, in 2023, South Africa still ranks third on the list of high-crime countries in the world, only after Venezuela and Papua New Guinea (World Population Review, 2023). According to the official crime statistics, the country has exceedingly high rates of assaults, rape, homicides, and other violent and property-related crimes, especially burglaries (South African Police Service, 2023). The economic cost of crime in South Africa has been estimated at 10% of GDP per year (World Bank, 2023a, 2023b). However, this estimated cost does not include the intangible costs of indirect welfare reductions due to victimization. Our results are meant to shed some light on such costs. High-profile cases of violent crime, such as the surge in murders and assaults, highlight the severe personal and societal costs. For instance, the South African Police Service reported over 21,000 murders in 2019 alone, making the murder rate five times the global average. Additionally, the pervasive fear of crime has been shown to decrease productivity and deter investment, further exacerbating economic disparities and hindering social development (World Bank, 2023a, 2023b). These examples underscore the critical need to understand and quantify the personal costs of crime victimization, providing a foundation for targeted policy interventions. Thus, informed evaluations of the efficacy and effectiveness of policy responses and interventions in this context are crucial. The effect of crime on life satisfaction is more likely to be of a different magnitude in developing countries than in developed ones, and in high-crime contexts than in low-crime contexts. Studying this relationship in a high-crime country such as South Africa thus facilitates increased quality of policy making in areas where concerns on the topic are the greatest in addition to its scientific contribution. Powdthavee (2005) is the only study that has been conducted in South Africa on the cost of crime victimization, but it uses data collected more than two decades ago.

Specifically, we contribute to the literature on the economic valuation of crime victimization and the literature on the determinants of subjective well-being. Beside the practical importance of examining this topic in high-crime, high income-inequality settings, we make two methodological contributions. First, we model well-being using the personal well-being index (PWI) as a utility proxy, and we compare results with models using the general life satisfaction question and the global happiness question to measure well-being. The PWI is based on eight life-satisfaction questions measuring different aspects of well-being (International Wellbeing Group [IWG], 2013). Previous studies estimating the WTP for crime victimization only use one life-satisfaction or happiness as-a-whole question (e.g., Ásgeirsdóttir, Hardardottir, and Jonbjarnardóttir, 2023; Spencer & Liu, 2019; Manning et al., 2016; Cheng & Smyth, 2015; Kuroki, 2013; Cohen, 2008). The PWI used in the South African Social Attitude Survey (SASAS) consists of eight life domains which are the first-level deconstruction of life satisfaction as a whole (Cummins et al., 2003). Being developed from the Comprehensive Quality of Life Scale (ComQol) (Cummins et al., 1994), which includes both subjective and objective quality-of-life measures, the PWI has been validated in various countries (e.g., McIntype, Saliba, and McKenzie, 2020; Gallardo-Peralta et al., 2019; Jovanovíc et al., 2019; Cacas et al., 2012; Tomyn & Cummins, 2011; Yiengprugsawan et al., 2010; Tilioune et al., 2006), and it has been recommended for measuring subjective well-being by the OECD (2013) and the WHO (2013). The relationship between wellbeing proxies and utility remains debated between economists and psychologists (Kimball & Willis, 2023). This is the first paper to include the PWI in the comparison with other utility proxies that are used in the CIV literature.

Second, previous studies (Ragnarsdóttir et al., 2023; Ásgeirsdóttir et al., 2021; Ólafsdóttir et al., 2020) indicate that CIV results are sensitive to the functional form of income and that high CIV values can be quite unrepresentative for the median voter and largely driven by high-income individuals with very low marginal utility of income. This is particularly important to keep in mind given the extreme income inequality within South Africa. Thus, we allow for a piecewise linear (PWL) relationship for income, in addition to using its natural logarithm, to calculate CIV measures for each income group and to reduce the effects of outliers.

2 Methods

2.1 Data

We use seven waves of SASAS data collected in 2009, 2010, 2011, 2015, 2016, 2017, and 2018, which contain four utility proxies and other variables for the analysis. Available data collected in 2012, 2013, and 2014 lack observations on key variables of interest, such as crime victimization and happiness, and are therefore excluded from our study. SASAS is a nationally representative, repeated cross-sectional survey, which has been conducted by the Human Sciences and Research Council (HSRC) to measure changes in social attitudes and values in South Africa since 2003. SASAS covers different topics, such as democracy and governance, national identity and pride, intergroup relations, immigrant related attitudes and behaviours, education, personal well-being, crime and safety, poverty, taxation, respondents' and households' characteristics, income (HSRC, 2021). The PWI was added to the survey in 2009. We therefore do not use data collected before 2009.

Summary statistics for all variables are presented in Table 1. About 25% of the respondents reported that they themselves or their family members have been assaulted or burglarized in the last five years. The average equivalized household income per year, after being adjusted for inflation, is almost USD 4000. The income distribution is skewed right, and there is a substantial statistical difference in income between males and females. The mean age of the sample is 42 years old, and a majority (64%) are black Africans. Nearly half of the respondents have never married, while a majority (78%) has completed at least secondary education. The unemployment rate among the respondents is quite high (32%). The average number of members in each household is four, and nearly two thirds (62%) of the respondents live in formal urban areas.

2.2 Variables

With respect to the utility proxy, SASAS contains one general happiness question and two general life satisfaction questions, as well as the PWI scale that is composed of eight questions on different life-satisfaction domains (henceforth domain question), including standard of living, health, achieving in life, personal relationships, safety, community connectedness, future security, and spirituality or religion (HSRC, 2021). The happiness question and the first general life-satisfaction questions use a five-point response scale ranging from 1 (very dissatisfied/unhappy) to 5 (very satisfied/happy). The second general life satisfaction question, which is not a component of the PWI (IWG, 2013) uses an 11-point response scale. Respondents can choose a number from 0 to 10, where 0 means 'completely dissatisfied' and 10 means 'completely satisfied'. The PWI, is calculated

Table 1 Summary statistics by gender (mean and standard deviation in parentheses)

Variable	Males (N = 5927)	Females (N = 9154)
General life satisfaction[a] (5-point scale)	3.21 (1.19)	3.12 (1.20)
General life satisfaction[a] (11-point scale)	6.13 (2.49)	5.97 (2.49)
PWI[a,b](11-point scale)	6.34 (1.66)	6.20 (1.64)
Happiness[a] (5-point scale)	3.42 (1.13)	3.37 (1.15)
Crime victimization	24.71 (43.14)	22.87 (42.00)
Income[c]	5004 (7628)	3260 (5472)
Age	41.84 (16.72)	43.05 (16.84)
Black African %	61.36 (48.69)	66.05 (47.35)
Coloured %	15.18 (35.89)	16.57 (37.18)
Indian %	12.80 (33.41)	10.10 (30.14)
White %	10.62 (30.82)	7.25 (25.93)
Married %	41.89 (49.34)	34.20 (47.44)
Separated %	1.73 (13.06)	2.68 (16.17)
Divorced %	3.20 (17.61)	3.77 (19.07)
Widowed %	5.48 (22.76)	15.07 (35.78)
Never married %	47.68 (49.95)	44.25 (49.67)
No schooling %	3.39 (18.10)	6.03 (23.80)
Primary %	15.35 (36.05)	18.34 (38.70)
Secondary %	33.50 (47.20)	37.90 (48.51)
Matriculation exam[d] %	30.82 (46.18)	26.99 (44.39)
Tertiary %	16.92 (37.49)	10.72 (30.94)
Employed full time %	34.82 (47.64)	17.90 (38.34)
Employed part time %	6.71 (25.03)	4.82 (21.43)
Employed less than part time %	2.14 (14.48)	1.93 (13.77)
Temporarily sick %	0.57 (7.55)	0.39 (6.25)
Unemployed, not looking for work %	4.50 (20.74)	7.64 (26.57)
Unemployed, looking for work %	23.43 (42.36)	28.39 (45.09)
Pensioner (aged/retired) %	15.40 (36.10)	17.16 (37.70)
Permanently sick or disabled %	2.02 (14.08)	1.69 (12.90)
Housewife, not looking for work %	0.20 (4.49)	7.17 (25.81)
Housewife, looking for work %	0.25 (5.02)	4.20 (20.07)
Student/learner %	7.45 (26.27)	7.20 (25.86)
Household size	3.47 (2.12)	4.22 (2.44)
Urban, formal %	64.34 (47.90)	60.96 (48.78)
Urban, informal %	7.13 (25.74)	7.40 (26.18)
Traditional authority area %	19.18 (39.37)	24.71 (43.13)
Rural, formal %	9.33 (29.08)	6.91 (25.37)

[a]In the analysis, four utility proxies are standardized to having a mean of zero and a standard deviation of one in the analysis

[b]The PWI is calculated as an average of the respondent-level data on eight domain questions, incl. standard of living, health, achieving in life, personal relationships, safety, community connectedness, future security, and spirituality/religion, all answered on a 11-point scale (HSRC, 2021)

[c]Yearly equivalized household income adjusted by inflation and converted to 2018 USD

[d]Final year of high school (Grade 12) in the South African education system

as an average of the respondent-level data on eight domain questions, all answered on a 0–10 point scale (IWG, 2013). To ease the comparison between these measures, we standardize them all to having a mean of zero and a standard deviation of one.

Our measure of crime victimization is a yes or no response to the question, '*Have you or a member of your household been the victim of burglary or assault in the last five years?*' Three things need to be kept in mind regarding this measure. First, this measure includes any household member's victimization, not necessarily the respondent's own experience. This is important for the interpretation of our results. We acknowledge that if the reader is particularly interested in the respondent's own crime victimization, this approach might lead to an underestimation of the WTP, as the psychological and emotional impact of direct victimization can be significantly higher than indirect victimization. Interpreted through the lens of own victimization, our results should be seen as a lower bound. However, a more accurate interpretation of our results is that they capture the vulnerability and insecurity associated with close proximity to burglary or assault, regardless of whether the individual has been directly victimized. Second, we acknowledge that not all crimes are reported, which can lead to underestimation of the true extent of crime victimization. This underreporting is a common issue in crime studies and can result from various factors such as fear of retaliation, distrust in law enforcement, or the perception that the crime is not serious enough to report (Fisher, 1993; Raphael, 1987). To mitigate the impact of underreporting, our analysis includes a broad measure of victimization within the household, capturing both direct and indirect experiences. Additionally, we interpret our WTP estimates as conservative figures that likely underestimate the true societal costs of crime victimization. Lastly, this question captures the experience of crime victimization in a five-year period which is longer than the one-year period used in previous studies (e.g., Cheng & Smyth, 2015; Spencer & Liu, 2019). However, such responses might be subject to certain biases, including recall bias (Raphael, 1987) and social-desirability bias (Fisher, 1993), potentially leading to the underestimation of regression parameters (Althubaiti, 2016) and in turn an attenuation bias in CIV estimates.

For income, SASAS respondents are asked to report both household income and personal income. We follow the literature and select household income for the analysis (Baldursdottir et al., 2023a, bÁsgeirsdóttir et al., 2021; Ólafsdóttir et al., 2020; Howley, 2017; Brown, 2015; Cheng & Smyth, 2015; Kuroki, 2013; Moore & Shepherd, 2006). This is done for several reasons, including to best capture individuals' access to finance and to reduce the endogeneity bias in the income coefficients which are likely to be greater if using own-labour-market income in a life-satisfaction equation. The household income is obtained from the question, '*What is the total monthly household income of all the people in your household before tax and other deductions?*' There are 15 answer options ranging from no-income to more than or equal to ZAR 50,001 (USD 3779). Also, respondents can refuse to answer or select the do-not-know option. We code the responses by taking the midpoint of each range. For the highest income response, we code it as ZAR 60,000, which is based on the midpoint of the range of the preceding response (ZAR 30,001 – ZAR 50,000). We adjust the results to the 2018 price level using the consumer price index (CPI) and the official exchange rate of one USD being equal to ZAR 13.23 (World Bank, 2023a, 2023b). Given the difference in the composition of households in the sample, we standardize the household income variable using the OECD modified equivalence scale. Due to restrictions in the dataset, we define household members aged 14–15 as children, while they are adults as per the OECD's definition. We multiply income by 12 to derive yearly income for each household.

As control variables, we use respondents' characteristics (age, age squared, gender, race, marital status, education, employment), households' characteristics (household size, geographic location), and wave dummies to account for other factors that may influence life satisfaction and wave-specific effects. We include age squared because of the U-shaped relationship between age and well-being (Fritjers and Beatton, 2012). A more detailed description of the variables used in our analysis can be found in Table S2 (Supplementary materials). Our original dataset contains 21,652 respondents. Excluding observations based on measurement errors, missing values, and do-not-know responses in any variables selected for analysis, the final sample includes 15,081 respondents: 5927 males and 9154 females. We show the sources of this attrition in Table S3 (Supplementary materials). We furthermore compare summary statistics from the unrestricted data and the analysed subsample in Table S4 (Supplementary materials) to determine possible biases due to the attrition, for example, whether crime victimization is underreported. This comparison does not raise cause for alarm. Most notable is the income variable, which has the greatest number of missing values, but the mean and standard deviations reported in Table S4 appear unaffected.

2.3 Methods

To estimate the WTP for not being a crime victim, we assume that life satisfaction or individual utility, U, is determined by income Y, crime victimization C, and other individual and household characteristics X:

$$U = U(Y, C, X) \tag{1}$$

where C denotes whether any household member, including the respondent, has been assaulted or burglarized over the past five years, and Y is the equivalized (yearly) household income. Individual utility is assumed to be a linear function of log income, crime victimization, and other individual characteristics (Cheng & Smyth, 2015; Moore & Shepherd, 2006). As we cannot observe individual utility directly, we estimate the following empirical model:

$$U* = \beta_0 + \beta_1 logY + \beta_2 C + \beta_3 X + \varepsilon \tag{2}$$

where U^* is a utility proxy (specifically happiness, life satisfaction, or PWI), β_0 is a constant, β_1, β_2, β_3 are the coefficients that measure the relationship between the utility proxy on one hand and income, crime victimization, and other individual and household characteristics on the other hand. Finally, ε is an error term that is assumed to be normally distributed. Log income is used in Eq. (2) to account for the diminishing marginal utility of income.

We also use income in its piecewise linear (PWL) form to account for heterogeneity across income groups, whilst still allowing for diminishing marginal utility of income (Ragnarsdóttir et al., 2023; Ásgeirsdóttir et al., 2021; Ólafsdóttir et al., 2020). We split the income data into three equal parts or terciles based on the number of observations. We identify two breakpoints (BP) of the income variable where the terciles meet: BP1 (USD 1153 for males and USD 830 for females) and BP2 (USD 3779 for males and USD 2,180 for females). The empirical specification of the utility function becomes:

$$U^{*}=\begin{cases}\beta_{10}+\beta_{11}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{1}, ifY\leq BP1(i)\\ \beta_{20}+\beta_{21}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{2}, ifBP1<Y\leq BP2(ii)\\ \beta_{30}+\beta_{31}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{3}, ifBP2<Y(iii)\end{cases} \tag{3}$$

in which the following conditions must be met:

$$\begin{array}{c}\beta_{10}+\beta_{11}\mathrm{BP1}=\beta_{20}+\beta_{21}\mathrm{BP1}\\ \beta_{20}+\beta_{21}\mathrm{BP2}=\beta_{30}+\beta_{31}\mathrm{BP2}\end{array} \tag{4}$$

The following PWL model is specified by inserting (4) in (3), which results in:

$$U^{*}=\begin{cases}\beta_{10}+\beta_{11}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{1}, if\ (i)\\ \beta_{10}+BP1(\beta_{11}-\beta_{21})+\beta_{21}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{2}, if\ (ii)\\ \beta_{20}+BP2\left(\beta_{21}-\beta_{31}\right)+\beta_{31}Y+\beta_{2}C+\beta_{3}X+\varepsilon_{3}, if\ (iii)\end{cases} \tag{5}$$

We use four utility proxies when estimating Eq. (2) and Eq. (5), specifically the five-point general life satisfaction scale (GLS5), the 11-point general life satisfaction scale (GLS11), the PWI, and the five-point global happiness scale (Happiness). We treat these proxies as continuous variables in their standardized form and use OLS for all estimations.

The CIV calculated from Eq. (2) is:

$$CIV=\left(\exp\left(-\frac{\beta_{2}}{\beta_{1}}\right)-1\right)*\overline{\mathrm{Y}} \tag{6}$$

where $\bar{Y}$ is the average equivalized household income in the sample, which is different between males and females. To address the endogeneity of income, we follow the literature (e.g., Ásgeirsdóttir, Hardardottir, and Jonbjarnardóttir, 2023; Ásgeirsdóttir et al., 2021) by adjusting our CIV estimates using results from previous studies on the relationship between income and subjective well-being using instrumental variables. Specifically, Luttmer (2005) found that the instrumented income coefficient was 2.93 times larger than without being instrumented for. We use this multiplier to adjust our CIV estimates from OLS models.

$$CIV=\left(\exp\left(-\frac{\beta_{2}}{2.93\times\beta_{1}}\right)-1\right)*\overline{\mathrm{Y}} \tag{7}$$

The CIV from Eq. (5) for the first income spline is:

$$CIV_{spline1}=-\frac{\beta_{2}}{\beta_{11}} \tag{8}$$

For the second income spline, the CIV formula is:

$$CIV_{spline2}=-\frac{\beta_{2}+\beta_{21}BP1}{\beta_{21}+\beta_{11}} \tag{9}$$

And for the third income spline, it is:

$$CIV_{spline3} = -\frac{\beta_2 + \beta_{21}BP1 + \beta_{31}(BP2 - BP1)}{\beta_{31} + \beta_{21} + \beta_{11}} \tag{10}$$

We use the delta method to calculate the standard errors for the CIV estimates and the *segmented* package in R to estimate PWL models. For each utility proxy, we disaggregate results by gender, and we use robust standard errors to account for heteroscedasticity. We present 16 models in the main results, and furthermore conduct sensitivity tests and check for robustness in our results.

3 Results

3.1 Main Results

Our main results are presented in Table 2, including eight models using the logarithm of income and eight models using the PWL form of income. Coefficients for income and crime victimization are presented, together with robust standard errors in parentheses.

Most of the independent variables have expected signs. Equivalized household income has a positive relationship with life satisfaction, whereas the relationship between crime victimization and life satisfaction is negative. It is noteworthy that this relationship is substantially stronger for females than for males. This disparity can be attributed to both individual vulnerabilities and societal factors that make females more susceptible to the negative impacts of crime victimization. The relationship between age and life satisfaction is U-shaped, which is consistent with previous studies (Blanchflower & Oswald, 2008). Higher education and being married also have a positive relationship with life satisfaction. In South Africa, individuals married under the civil law had more freedom in choosing their partners and enjoyed more legal rights compared to those not married or married under the customary law (Powdthavee, 2005). The divorced or separated reported the lowest level of life satisfaction. Being coloured, Indian, Asian, or white is more likely to be associated with higher life satisfaction as compared to being black African. Full-time employment is associated with higher life satisfaction, whereas part-time or less than part-time employment is associated with lower life satisfaction. With respect to household characteristics, household size has a significantly positive relationship with life satisfaction. This could be understood because larger households often provide more opportunities for social interaction and emotional support, while responsibilities such as financial burdens, childcare, and household chores can be shared among more household members, reducing the workload and stress on any single member, thereby increasing overall life satisfaction. Households living in formal urban areas are also likely to be more satisfied than those living in informal urban areas, traditional authority areas, or rural areas (results not shown). There are several reasons that support this finding, including more economic opportunities in urban areas, better housing quality, social and recreational facilities, transport and connectivity. More recent years have higher average life satisfaction compared to the reference year (2009). This effect could be due to various unobserved factors such as economic development and social changes, but they do not significantly change CIV estimates.

Given that the utility proxies are standardized to a mean of zero and standard deviation of one, it is possible to compare coefficients across OLS or PWL models. Results show that models using the PWI have the highest predictive power based on R-squared values. Based on statistically significant results and excluding results of the OLS models using the PWI,

Table 2 Point estimates and corresponding CIV estimates by utility proxy

Panel A: OLS	Males				Females			
	GLS5	GLS11	PWI	Happiness	GLS5	GLS11	PWI	Happiness
Log income	0.183*** (0.014)	0.161*** (0.014)	0.160*** (0.014)	0.187*** (0.014)	0.163*** (0.011)	0.129*** (0.011)	0.161*** (0.011)	0.189*** (0.011)
Crime	-0.090*** (0.028)	-0.035 (0.028)	-0.174*** (0.028)	-0.025 (0.028)	-0.108*** (0.024)	-0.106*** (0.024)	-0.219*** (0.023)	-0.073*** (0.023)
CIV	3326** (1349)		10,285*** (3014)		3167*** (1009)	4242*** (1512)	9735*** (2223)	1581** (615)
Observations	5705	5705	5705	5705	8925	8925	8925	8925
R-squared	0.156	0.157	0.201	0.157	0.117	0.125	0.176	0.154
Panel B: PWL	**GLS5**	**GLS11**	**PWI**	**Happiness**	**GLS5**	**GLS11**	**PWI**	**Happiness**
1. spline	0.148*** (0.021)	0.410*** (0.072)	2.129*** (0.309)	0.493*** (0.134)	0.254*** (0.029)	0.490*** (0.143)	2.173*** (0.262)	0.396*** (0.055)
2. spline	0.033*** (0.033)	0.065*** (0.103)	0.244 (0.442)	0.113*** (0.137)	0.027*** (0.041)	0.261** (0.214)	0.522 (0.388)	0.123*** (0.084)
3. spline	0.005** (0.036)	0.003*** (0.105)	−0.007 (0.458)	0.008*** (0.019)	0.011 (0.042)	0.027*** (0.226)	0.075 (0.415)	0.013*** (0.090)
Crime	−0.110*** (0.033)	−0.096 (0.069)	−2.773*** (0.451)	−0.033 (0.032)	−0.130*** (0.028)	−0.259*** (0.059)	−3.601*** (0.374)	−0.086*** (0.026)
CIV spline 1	745*** (248)		1302*** (286)		512*** (127)	529** (210)	1656*** (265)	217*** (75)
CIV spline 2	7234*** (2365)				11,714** (5425)	1722*** (649)		2529*** (407)
CIV spline 3	63,811 (97,838)					27,913 (55,286)		36,288 (32,299)
Observations	5927	5927	5927	5927	9154	9154	9154	9154
R-squared	0.897	0.881	0.949	0.917	0.886	0.870	0.946	0.911

Standard errors are in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Respondents with no income are removed from OLS models to avoid log 0. All CIV estimates are reported in 2018 USD per year. Control variables are age, age squared, race (coloured, Indian, white), marital status (married), education (primary, matric, tertiary), employment (employed full time), household size, housing location (urban, formal), and wave dummies (2008 as reference). In Panel B, the spline coefficients and standard errors are multiplied by 1000. CIVs are not computed if the income or the crime coefficient is not significant our CIV estimates from log-income OLS models range from USD 1581 to USD 4242. The CIV estimates vary substantially across the models. In log-income models, females have higher CIV estimates than males, and results are statistically significant. This gender difference is largely driven by differences in the crime coefficients, rather than the income coefficients which are fairly stable across genders. The CIV estimates based on the PWI utility proxy in models using the natural logarithm of income are much larger than comparable estimates using the general life satisfaction scales (GLS5, GLS11) and the global happiness scale (Happiness). The crime coefficient is similarly substantially larger in models using the PWI as a utility proxy in CIV estimations. PWL models also show a large heterogeneity in WTP across income splines. CIV estimates for the first and second income splines are statistically significant in all PWL models for females. For the second income spline, CIV estimates are not statistically significant when using the PWI. The highest-income spline results in the highest CIV estimates, albeit not statistically significant. It is important to note that our crime measure includes both direct and indirect victimization experiences, and thus, the WTP estimates should be interpreted as capturing the broader vulnerability and insecurity associated with proximity to crime.

3.2 Sensitivity Analyses and Robustness Checks

We examine the robustness of our results through several tests and sensitivity analyses. First, we calculate variance inflation factors (VIF), of which high values indicate potential multicollinearity. Test results indicate low correlations. Second, as seen in Eq. 6, the calculation of the CIV depends on average income. Some may argue that variation in results across gender based on females having lower average income than males can lead to injustices. We thus also calculate the CIVs using the mean income of the whole sample, instead of using the mean income for males and for females separately. When doing this, the gender difference in CIV estimates increases (Table S5, supplementary materials). Third, we test different model specifications by removing individual and household characteristics one at a time. This results in lower R-squared values, suggesting that the model specifications in our main results are optimal. Fourth, we do our best to address income endogeneity in accordance with methods previously used in this literature and described in Ásgeirsdóttir, Hardardottir, and Jonbjarnardóttir (2023). We have explained this in detail in the methods section above. CIV estimates adjusted for income endogeneity range from USD 472 to USD 1078 as can be seen in table S5 in the Supplementary material. Fifth, we remove two items in the PWI measure regarding safety and future security, and the CIV estimates reduce by about 50 percent (Table S6, Supplementary material). This indicates the problem of endogeneity in the PWI, in which the two items of safety and future security in the PWI have increased concerns about crime victimization among respondents. Sixth, to account for the fact that crime may be biased towards a certain group, we create interaction terms between crime and other socio-demographic variables. Results (not shown here) show that most of these interaction terms are not statistically significant. Only the interaction term between Indian males and crime in OLS and PWL models using the 11-point general life satisfaction scale (GLS11) has a significantly negative coefficient, suggesting that, for Indian males, the negative impact of crime on life satisfaction is stronger compared to other race groups. Lastly, to further explore wave-specific effects, we add interaction terms between wave dummies and the income variable and the crime variable. However, these interaction terms are not statistically significant (results not shown here), suggesting that the effects of income and crime on life satisfaction, happiness or PWI do not vary significantly across the different years.

4 Discussion

Estimating the cost of crime victimization is important for the development of policies to reduce crime, especially in a developing country with high crime rates and a high level of income inequality like South Africa. In this study, we use the CIV method to estimate this cost in the form of yearly equivalized household income that individuals would be willing to sacrifice to avoid suffering the consequences of burglary or assault. Previous studies use the general life satisfaction question or the global happiness question to measure subjective well-being, yet it has been argued that such abstract questions may not capture enough information about different life components that contribute to the sense of well-being (Cummins et al., 2003, p. 164). Similarly, the OECD (2013) and WHO (2013) have suggested the use of PWI as a measure of subjective wellbeing. The SASAS data provide us a unique opportunity to examine robustness of CIV results based on which utility proxy is used. We thus compare estimations based on the PWI, happiness, or life satisfaction, as well as examining the sensitivity of results based on the number of answer options on the life satisfaction scale.

Our results show that models using the PWI have higher predictability compared to models using other utility proxies. However, these models produce much higher CIV estimates. This is because the PWI is based on eight questions including two about safety and future security (HSRC, 2021). This scale, with two questions related to safety and security, has overemphasized this aspect, resulting in inflated estimations of the relationship between wellbeing and crime victimization. Our sensitivity analysis confirms this by removing two questions from the PWI. Another composite indicator of life satisfaction that has been widely used in subjective wellbeing research is the Satisfaction With Life Scale (SWLS), which was introduced by Diener et al. (1985). The SWLS contains five generic scales measuring satisfaction with life as a whole (Pavot & Diener, 2008). Unlike the SWLS, the PWI is composed of questions about very specific aspects of life. Our results suggest that the PWI may not be suitable for CIV research on topics that are covered in the PWI (incl. standard of living, health, achieving in life, personal relationships, safety, community connectedness, future security, and spirituality/religion). While overemphasis on specific aspects of life is at the expense of underestimating other aspects of life, the PWI could nonetheless be explored in studies on unrelated topics as it might increase the predictive power of models.

While the relationship between crime victimization and life satisfaction is negative, as expected, it is noteworthy that this relationship is substantially stronger for females than for males. This gender difference may be attributed to several factors. Females are generally more likely to experience fear of crime and the psychological impacts of victimization more intensely than males. Research indicates that women often perceive themselves as more vulnerable to crime, which can lead to heightened stress and anxiety. Furthermore, it could be that females are more likely to share their crime experience with others, while males are less likely to admit their fears of crime (Gilchrist et al., 1998; Walklate, 1997). Additionally, societal and cultural factors might play a role. Women are often socialized to be more attuned to personal security concerns, which can amplify the emotional impact of victimization (Lorenc et al., 2012). Furthermore, the consequences of crime, such as physical injury or the fear of repeat victimization, can be more disruptive to the daily lives of women, affecting their well-being more severely (Roberts, 2011). These factors could contribute to a stronger negative impact on life satisfaction for females compared to males and their exploration in this context would be a worthwhile exploration for future research. Our results also show a large difference in the crime coefficients across the OLS models and the PWL models. This can be explained by the difference in the dependent variable, which is on a different scale and a different variable in each estimation. The crime coefficients, therefore, are of different sizes because they are measuring effects on different outcome variables. The range of the difference is larger in the PWL models compared to the OLS models. This is possibly because the PWL models better capture heterogeneity across income groups than the OLS models.

Our CIV estimates based on log-income estimations (USD 1581–4242), is similar to the range of CIV estimates in Jamaica (USD 1266–4871), an upper-middle income country with high crime rates like South Africa, although these estimates are for not suffering any type of crime in the past 12 months (Spencer & Liu, 2019). With the PWL form of income, our CIV estimate ranges from USD 217 to USD 745 for the low-income group and from USD 1722 to USD 11,714 for the middle-income group. These ranges do not include estimates from models using the PWI and those that are not statistically significant. Our estimate for the highest income group are not statistically significant. The large heterogeneity of WTP between income groups highlights the income gap in South Africa and shows how much the highest income group influences the CIV estimates that are not stratified by income. Results based on different forms of income suggest that the high-income group might be inflating the CIV estimates, and that policy makers should be aware of that as regular CIV estimates can potentially be higher than what the median voter would be willing to pay.

In a previous study in South Africa, Powdthavee (2005) used data from the October Household Survey study in 1997, which is now quite dated. He produced a significantly higher estimate of USD 266,659, which is the compensating expenditure variation (CEV), or the expenditure required to compensate an average household for a reduction in well-being as a result of crime victimization. Besides burglaries, his estimates also include the cost of any household member being murdered, which is a serious crime. Powdthavee (2005) used the measure of perceived quality of life at the household level, which is captured by the question, '*Taking everything into account, how satisfied is this household with the way it lives these days?*' Although his methods should conceptually be similar, it is difficult to say if any found differences stem from those differences in methods. The difference between Powdthavee's estimates and ours may be attributed to variations in the types of crime examined, with his exposure representing more serious victimization. Not least, the difference is likely to be due to whether or not income endogeneity was accounted for in the analysis. As can be seen in Table S5 (Supplementary materials), our CIV estimates are on average four times larger when not adjusted for income endogeneity. Powdthavee does not make such adjustments and thus his results would be most comparable to our unadjusted results. However, it should be noted that even if a comparison is made with our unadjusted results, his remain substantially larger than ours. It is easy to argue that his estimates could be unreasonably large, but according to his estimates an average household would require a financial package worth 82 times of their current spending to make them feel indifferent about their crime experiences. In contrast our CIV estimates, using life satisfaction questions and thus most comparable to Powdthavee, are around or below yearly income, and only around four times yearly income when unadjusted for income endogeneity.

In the third study conducted in developing countries, Cheng and Smyth (2015) estimated a CIV of USD 1584, which is within the range of Spencer and Liu's estimates (USD 1266-4871) and ours (USD 1581-4242). Cheng and Smyth (2015) used household income per capital and examined a range of crime in China, including out-of-home theft, out-of-home robbery, home burglary, home robbery, assault, and threat. Previous studies on high-income and low-crime countries produced much higher CIV estimates (see Table S1, Supplementary materials). For instance, Ásgeirsdóttir et al. (2023) estimated the CIV for different types of violent crime in Iceland, including psychological violence (USD 44,581), sexual violence (USD 22,623), and physical violence (USD 11,145). Johnston et al. (2018) estimated the lifetime cost of USD 69,047 for violent crime in Australia. Kuroki (2013) produced a CIV estimate ranging from USD 37,268 to USD 55,902 for burglary and robbery in Japan. Santos (2013) estimated the CIV for violent crime in the UK to be USD 47,284. However, it should be noted that of course income levels are much higher in those countries. This highlights the difficultly in using CIV estimates from one context for policy evaluations in a different setting. Studies from different social, cultural, and institutional settings are thus needed.

Other findings on the relationship between control variables and life satisfaction generally resonate the findings of previous studies in South Africa (Møller, 2005; Powdthavee, 2005; Roberts, 2011). However, endogeneity issues are difficult to tackle in this field. Higher income individuals might, for example, choose to live in areas with a lower crime rate. Of the 11 studies estimating the cost of crime victimization (see Table S1, supplementary materials), only four address the endogeneity issue is some sense, albeit often indirectly. In this study, we also address this issue following methods that have previously been used in the literature. Given that most of the literature, especially within high-crime low-and-middle-income countries does not adjust for income endogeneity, unadjusted results may be most beneficial for comparisons to the literature. However, policy makers wishing to use the results as guidance for interventions are referred to our endogeneity-adjusted results.

Our results have two policy implications, despite the limitation of potential underreporting of crimes and some crime exposure representing indirect victimization. First, even with conservative estimates, the cost of being burglarized or assaulted is high across income groups, suggesting that there could be net benefits from the government's higher investments in policies and interventions to reduce burglaries and assaults. This is highly relevant to South Africa where the rates of burglary and assault are particularly high (South African Police Service, 2023). Second, it is important to interpret our results carefully to avoid the implication that higher-income individuals should be protected more due to their higher WTP for avoiding victimization. The higher willingness to pay observed among higher-income groups is a reflection of their greater financial capacity (represented by the income coefficients) rather than a greater impact of crime victimization (represented by the crime coefficient). The importance of equitability in policy interventions and avoiding disproportionately favouring wealthier individuals should be balanced against our results. Naturally, authorities implementing balanced policies consider the overall vulnerability and access to protective measures when developing interventions. Although the higher-income groups are willing to pay more to avoid the negative consequences of burglary or assault, they are more capable of protecting themselves from burglaries, for instance through installing home security systems, or covering healthcare costs in the event of an assault.

Our results also provide implications for developing crime-reduction strategies and interventions. Initiatives such as installing CCTV or deploying community-based patrol groups in lower-income areas could be particularly relevant in the South African context. Additionally, offering better healthcare services or clinical support to assault victims could help alleviate the negative impacts. The government of South Africa has recently developed a crime fighting plan, which focuses on increasing the number of police officers and establishing specialized teams trained to tackle specific types of crime. The government also plans to use data-driven methods to identify and target crime hotspots (South African Government, 2024). But many other potential policies are possible, such as implementing awareness raising, educational, and social programs to address the root cause of crime. These efforts could include providing education, increasing employment opportunities, and improving social and economic conditions for youth and marginalized groups, gun-control policies, and re-entry programs for past offenders. Given that the relationship between crime victimization and wellbeing measures is stronger for females than for males, it would be worthwhile to explore the efficiency of crime-reduction strategies and interventions specifically designed for women, such as self-defense training programs for women and establishing specialized teams focusing on crimes against women such as sexual assault or domestic violence.

Having said that, policy is generally not made directly based on WTP estimates. However, such estimates are important inputs into subsequent cost–benefit analyses of interventions, allowing for the inclusion of indirect and intangible costs such as suffering due to victimization. We thus encourage further analyses that incorporate these estimates to inform comprehensive and effective policy decisions.

5 Conclusion

This study is the first to investigate the relationship between victimization of burglary or assault, income, and subjective well-being using the PWI as a utility proxy. There are four major findings. First, models using the PWI as a utility proxy have higher predictability than those using the general life satisfaction question or the global happiness question. However, the PWI significantly drives CIV estimates upwards, possibly due to the construction of the scale and overemphasis on safety and security. That would make the PWI unsuitable for CIV research on crime victimization and possibly on other topics covered in the PWI. Second, there is significant heterogeneity of the WTP across income groups, providing important implications for policy makers. Third, PWL models provide more information, especially in countries with high levels of income inequality. Our estimates of the utility penalty associated with crime victimization are much smaller than previously found for South Africa using household expenditure data from 1997 and one single life satisfaction question (Powdthavee, 2005). We have compared different utility proxies and estimated the WTP for different income groups using newer data than previously done for South Africa. Similarly, we have addressed income endogeneity, not addressed before. Our results can be used in the evaluation of strategies and interventions to reduce burglaries and assaults in South Africa.

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Code availability The R script used in this study is available from the authors upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval This study uses available datasets collected from surveys that have been ethically approved.

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