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Effects of Happiness on Income Generation and Inequality

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Abstract: This paper examines how happiness affects the income generating capacity of individuals and thereby the distribution of income. It is hypothesized that happiness impacts upon the income generating capacity of individuals directly by stimulating work efficiency, and indirectly by affecting their allocation of time for paid work. Both these effects of happiness on income are tested in a model consisting of an income generating function and a work-hour equation. The Australian panel survey data from the first 14 Waves of HILDA (2001-2014) are used to estimate the model. The income flows of happiness and other variables obtained from the model are inserted into the inequality decomposition equations (rules) to obtain their relative contributions. The study concludes that happiness has a positive and significant effect on income generation and contributes to the reduction of inequality in Australia.

Key words: Happiness, Health, Income inequality, income generating model

JEL Codes: C23, C51, D31

Effects of Happiness on Income Generation and Inequality

1. Introduction

The question of whether income has any effect on happiness (life satisfaction) is a long-studied issue in economics, psychology, and other social sciences. Across multiple studies, the effect of income on happiness has been found to vary from positive to insignificant (Frijters et al., 2004; Deaton, 2008; Graham, 2010; Paul and Guilbert, 2013). Based on data from the Gallup World Poll for the US, Kahneman and Deaton (2010) observed that emotional well-being[1] rises with income, but this relationship is subject to diminishing returns, with hardly any progress in emotional well-being beyond an annual income of US$75,000 in 2008.[2] Binder and Coad (2011) apply quantile regressions to data from the British Household Panel Survey of 2006 and find that income has a stronger effect on happiness at the lower end of the happiness distribution than at the upper end of the happiness distribution.[3] These results indicate that rising income has a positive but marginally diminishing effect on happiness.

However, relatively little attention has been paid to whether happier individuals perform better financially. This reverse causality is under-studied. Using the Household, Income and Labour Dynamics in Australia (HILDA) panel survey data, this paper examines the causality running from happiness to income generation and explores the effects of this relationship on inequality. This research is not intended to undermine the literature on the

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[1] Emotional well-being refers to the emotional quality of an individual's everyday experience of joy, stress, sadness, anger, and affection that makes one's life pleasant or unpleasant, see Kahneman and Deaton, 2010, p. 16489.

[2] This threshold level of income is also confirmed in a recent study by Hodge and Shankar (2016).

[3] Using data for the world, the EU-15 countries and Latin America and the Caribbean, Graham and Nikolova (2014) also estimated the quantile regressions with self-reported life satisfaction as well as hedonic well-being as the dependent variables and obtained results which are similar to those reported in Binder and Coad (2011).

effects of income on happiness. Rather, the purpose is to make a case for a reverse causality and explore its implications for income distribution.

A causal effect running from happiness to income could arise for a number of reasons. There is an extensive literature in psychology revealing that happiness has several correlates such as self-esteem, creativity, discipline, and cognitive abilities, which in turn are known to influence labour market outcomes. Happy individuals have higher self-esteem and are more disciplined in their activities (Frank, 1997; Kenny, 1999). Happiness stimulates creativity (Amabile et al., 2005), boosts cognitive flexibility by broadening focus and attention (Isen, 2008), and improves economic and strategic decision making including the reallocation of time from less interesting tasks to more rewarding ones (Hermalin and Isen, 2000; Isen and Reeve, 2005; Lyubomirsky et al., 2005; Ifcher and Zarghamee, 2011). More recently, neuroscientific research suggests that greater subjective well-being is associated with neurological variation, which, in turn, is associated with improved cognitive skills and economic outcomes (De Neve and Oswald, 2012). These results provide reasons to believe that there could be an effect running from subjective well-being to economic outcomes.

Several studies have examined the effects of happiness on life domains such as marriage as well as on consumption, savings, and investment behaviour (Binder and Coad, 2010; Guven, 2012; Rao et al., 2014). In an experimental study, Oswald et al. (2008) induced variation in positive mood and found that it can predict productivity levels. The effects of happiness on human performance are also observed across divergent work environments. For instance, happy cricket players show superior performance during games compared to less happy players (Totterdell, 1999, 2000), and insurance agents with a positive disposition have been found to sell more insurance policies than their less positive counterparts (Seligman and Schulman, 1986). On the other hand, Sanna et al. (1996) suggest that individuals experiencing negative mood[4] tend to put forth the most effort. This is consistent with the commonly held view that academics produce a larger and

[4] Negative mood refers to the state of unhappiness.

higher quality research output when they are under pressure to attain tenure at the North American Universities[5].

These studies are important because they point toward a potential role for happiness in shaping socio-economic outcomes. A handful of studies have tried to estimate the effect of happiness on future income. Diener et al. (2002) observed a positive correlation between "cheerfulness" measured in a sample of elite college students and their income levels some 19 years later. This association was found to be particularly important for those with a below-average level of cheerfulness. Based on panel data for Russia, Graham et al. (2004) examined whether happiness levels in 1995 had any impact on income levels in 2000. Happiness, which was measured on a scale numbered from 1 (not at all happy) to 5 (completely happy), was regressed on log household equivalence income and other conventional variables using data for 1995; and the residual happiness was obtained as the difference between observed happiness and estimated happiness. The log household equivalence income in 2000 was then regressed on residual happiness in 1995. The study reported that a 1-point increase in the unexplained (residual) happiness in 1995 yields approximately a 3 per cent increase in household equivalent income in 2000.

De Neve and Oswald (2012) use data from a large US representative panel and show that adolescents and young adults who report higher life satisfaction or positive affect[6] grow up to earn significantly higher levels of income one decade later in life. A few other studies have revealed that individuals tend to have a 'baseline' or 'set point' happiness level that shows persistent strength over time (Diener and Lucas, 1999; Bartels and Boomsma, 1999). More recently, De Neve (2011) has identified a gene, called 5-HTTLPR, which explains the variation in baseline levels of happiness.[7]

If happiness has a significant effect on income, then variations in happiness levels among individuals are likely to affect the distribution of income in society. This has not yet been

[5] A similar view is expressed in Miller et al. (2011).

[6] Positive affect refers broadly to the feeling of happiness.

[7] Also, see De Neve et al. (2012).

explored in the literature. The present study fills this gap. We posit that happiness impacts upon the income generating capacity of individuals directly by stimulating their work efficiency and indirectly by affecting their allocation of time for paid work. Both these effects of happiness on income generation are tested in a model consisting of an income generating function and a work hour equation. The model is estimated using the panel data from the first 14 Waves (2001-2014) of the HILDA surveys. The income flows of happiness and other variables such as age, health, sex, and occupations derived from the model are inserted into the inequality decomposition equations (rules) to obtain their relative contributions. The empirical results reveal that happiness has a positive and significant effect on income generation and contributes to the reduction of inequality in Australia.

The rest of the paper is organised as follows. Section 2 discusses the analytical framework which consists of an income generating model and the inequality decomposition methodology. Section 3 describes the data and variables. The empirical results are discussed in Section 4. Section 5 summarises and brings together the conclusions.

2. The Analytical Framework

The analytical framework chosen for this study comprises of two steps. The first step explores the channels through which happiness may affect the income-generating capacity of an individual. It is posited that happiness directly enhances the performance of an individual in earning activities. This will be referred to as the direct or productive effect of happiness on income generation. Happiness may also affect income indirectly via its impact on the allocation of time for paid work. An individual allocates her total time between three activities: (i) paid work, (ii) maintenance of health (such as sleeping and resting), and (iii) consumption of relational goods. An individual works for some hours in the week to earn income required for purchasing conventional consumption goods. Everyone devotes some minimum time for maintaining health. The relational goods are the interactions with family members, friends, and relatives. These goods are time consuming and thus have opportunity cost, but they are jointly produced and are known to be beneficial to individuals. People go on holidays to recharge their energy essentially by consuming relational goods. People also consume 'relational bads' while interacting with some unpleasant colleagues and customers at work or with unknown individuals in the market place. A happy person may prefer to work more hours per week, leading to increased production and earnings. Or, alternatively, a happy person may like to enjoy more leisure time to consume relational goods and thus work fewer hours per week. The resulting income loss is the opportunity cost associated with consuming relational goods (leisure). This will be referred to as the indirect effect of happiness on income.

The total effect of happiness on income will depend on the magnitude and signs of both the direct and indirect effects. If the direct effect is positive and the indirect effect is negative, the net effect on earnings should be positive (negative) if the former effect is stronger (weaker) than the latter. If happier people are more productive and work more hours, then the happiness-induced effect on income generation is expected to be stronger. Similarly, poor health and being female may also have direct and indirect effects on income. Poor health is likely to reduce not only the productivity of a worker but also her work hours.[8] Female workers may engage in work that is paid at a lower rate than their male colleagues, and they may also work fewer paid hours per week due to their greater involvement in household activities.[9] These effects are largely empirical in nature and hence will be tested in the proposed model discussed in Section 2.1.

The second step requires an inequality decomposition methodology to assign inequality contributions to income flows from happiness and other income generating variables. A

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[8] There is a vast literature which suggests that poor health adversely affects work capacity and income. See Leibenstein (1957), Harold (1975), Dasgupta (1997), Schultz and Tansel (1997), Ettner et al. (1997), Strauss and Thomas (1998), Currie and Madrian (1999) and Weil (2005).

[9] This may not be true for a country like the US where there is a sharp increase of women in the labor force and in (educated) females being the primary wage earners.

standard procedure is to choose one or more inequality measures which are decomposable by income flows (sources). Since inequality measures differ in terms of their distributional weights, their decomposition rules differ from each other. Hence, the choice of inequality decomposition measures becomes important for assigning unambiguous inequality contributions to different income flows. This issue is discussed in Section 2.2.

2.1 The Income Generating Model

Consider the following income generating function.

$$Y_{it} = \gamma_0 + \beta H_{it} + g(A_{it}) + x_{it}\gamma + s_i + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the total income of individual i during period t. H_{it} is the self-reported overall life satisfaction (happiness) taking values between 0 ('totally dissatisfied') and 10 ('totally satisfied') as reported in the HILDA surveys. The happiness scores are assumed to be the cardinal numbers. The function $g(A_{it})$ represents the individual's age-income profile and x_{it} is a vector of work-hours and binary variables such as education, gender, location, poor health, and occupation. The choice of these variables is guided by human capital theory as well as by the availability of data. The term, s_i, is the effect of time-invariant unobserved abilities (heterogeneity), and this is assumed to have zero mean and constant variance, σ_s^2. Finally, ε_{it} represents the general effect of transitory factors and is also assumed to have zero mean and constant variance, σ_ε^2. We further assume that the variance of the combined random term ($\varphi_{it} = s_i + \varepsilon_{it}$) is also constant, $\sigma_\varphi^2 = \sigma_s^2 + \sigma_\varepsilon^2$.

Human capital theory suggests a hump-shaped age-income profile, which is often represented by regressing log income on age and age^2 (see e.g. Murphy and Welch, 1992 and Willis, 1986). However, since we are interested in decomposing the inequality of income rather than of log income, the age-income hump profile is approximated by a piece-wise function of age - a procedure which is common in the literature (King and Dicks-Mireaux, 1982; Paul and Dasgupta, 1989). The function is assumed to consist of three pieces corresponding to three age groups, namely, (i) below 25, (ii) 25 and less than 35, and (iii) 35 and above. We specify linear forms for the first two age groups and a quadratic form for the third age group during which income reaches the maximum level and then starts declining. To ensure a smooth transition, the right-hand derivative of the second function will be equated to the left-hand derivative of the third function, both being evaluated at age 35. If we assume that the working age of an individual starts at 15 (which is the minimum age observed in our sample), then the hump-shaped pattern of the age-income profile can be specified as

$$g(A_{it}) = \alpha_1 V_{1it} + \alpha_2 V_{2it} + \alpha_3 V_{3it} \quad (2)$$

where A_{it} is the age of individual i during time-period t and

$V_{1it} = (A_{it} - 15)\, d_{1it} + 10\, (d_{2it} + d_{3it})$

$V_{2it} = (A_{it} - 25)\, (d_{2it} + d_{3it})$

$V_{3it} = (A_{it} - 35)^2\, d_{3it}$

with age dummies specified as

$d_{1it} = 1$ if $A_{it} < 25$, zero otherwise

$d_{2it} = 1$ if $25 \le A_{it} < 35$, zero otherwise

$d_{3it} = 1$ if $A_{it} \ge 35$, zero otherwise.

Substituting (2) and the elements of vector x_{it} into (1), we have

$$\begin{aligned} Y_{it} &= \gamma_0 + \beta H_{it} + \alpha_1 V_{1it} + \alpha_2 V_{2it} + \alpha_3 V_{3it} + \gamma_1 W_{it} \\ &+ \gamma_2 \text{Graduate}_{it} + \gamma_3 P_{it} + \gamma_4 \text{Female}_i + \gamma_5 \text{City}_{it} + \gamma_6 \text{Professional}_{it} \\ &+ \gamma_7 \text{White collar}_{it} + \gamma_8 \text{Blue collar}_{it} + \gamma_9 \text{Others}_{it} + s_i + \varepsilon_{it} \end{aligned} \quad (3)$$

where W represents the average work hours per week; Graduate, P, Female, City, Professional, White collar, Blue collar, and Others are the binary variables representing education, poor health, sex, living within a major city and occupational status[10]. Note that α_1, α_2 and $(\alpha_2 + 2\alpha_3 (A_{it} - 35))$ reveal the annual marginal changes in income during $15 \le A_{it} < 25$, $25 \le A_{it} < 35$ and $A_{it} \ge 35$ respectively. The coefficient β represents the efficiency (direct) effect of happiness on income generation. Poor health is expected to have an adverse effect on the productive efficiency of a worker.

In the above equation, happiness and work hours are time-varying endogenous variables, female is a time-invariant exogenous variable and all other variables are time-varying and exogenous. The equation is estimated with the Hausman and Taylor (1981) instrumental variable method (HT) using the command *xthtaylor* available in STATA. This estimation not only overcomes the problem of endogeneity but also accounts for the unobserved

[10] These variables are explained in Section 3.

heterogeneity (s_i). All the instruments used in the HT estimation are taken from within the model. All the time-varying exogenous variables deviated from their individual temporal means serve as instruments and similarly, all the time-varying endogenous variables deviated from their individual temporal means serve as instruments[11]. These instruments are quite strong as they exhibit sufficient within-panel variation (see Appendix Table A1). Since there is no time-invariant endogenous variable in the model, no other instruments were required[12].

As also discussed in the beginning of Section 2, happiness, poor health, and being female may also affect income indirectly through their impacts on work hours. To capture these effects, we specify a work-hour equation. In the absence of any guidance from economic theory, work hours, for the sake of simplicity, are assumed to be a linear function of happiness.

$$W_{it} = \phi_0 + \phi_1 H_{it} + \phi_2 P_{it} + \phi_3 Female_i + \eta_i + e_{it} \tag{4}$$

where η_i and e_{it} are respectively individual time-invariant and general random effects and are assumed to have zero mean and constant variance. Like equation (3), (4) is also estimated using the Hausman-Taylor method to account for the endogeneity of happiness. If ϕ_1, ϕ_2 and ϕ_3 are statistically significant, then the second, third and fourth terms in equation (4) will represent those portions of work-hours that are induced (or constrained) by happiness, poor health, and being female, respectively. The remaining part $(\phi_0 + \eta_i + e_{it})$ represents the 'obligatory-work-hours' (OW) of a healthy but 'totally unsatisfied' person.

[11] For example, ($H_{it} - H_i$) serves as an instrument for H_{it}, where H_i is the temporal mean. All other instruments are constructed in the same way.

[12] Once the instruments are specified, the *xthtaylor* command in STATA provides the HT estimates of equation (3). However, for the benefit of readers, we briefly outline the intermediates steps involved in the HT estimation. In step 1, the within estimator is used to obtain coefficients of time-varying exogenous and endogenous variables. Using these estimated coefficients, within residuals are obtained. In step 2, the within residuals are regressed on time-invariant exogenous variable, Female. In step 3, the variance components, σ_ε^2 and σ_s^2 , are calculated using the residuals from the above two regressions. These variance components are then combined to form weights. In step 4, equation (3) is transformed by multiplying the variables with these weights. The 2SLS is applied to this transformed equation using the set of instruments described in the text. This gives us the HT estimates which are consistent and efficient. For details, see Hausman and Taylor (1981).

Substituting (4) into (3) we have

$$\begin{aligned} Y_{it} &= \gamma_0 + (\beta + \gamma_1\phi_1)\,H_{it} + \alpha_1 V_{1it} + \alpha_2 V_{2it} + \alpha_3 V_{3it} + \gamma_1\,OW_{it} + \gamma_2\,Graduate_{it} \\ &\quad + (\gamma_3 + \gamma_1\phi_2)\,P_{it} + (\gamma_4 + \gamma_1\phi_3)\,Female_i + \gamma_5 City_{it} + \gamma_6\,Professional_{it} \\ &\quad + \gamma_7 White\ collar_{it} + \gamma_8\,Blue\ collar_{it} + \gamma_9\,Others_{it} + s_i + \varepsilon_{it} \end{aligned} \tag{5}$$

Note that β and $(\gamma_1\phi_1)$ are respectively the direct and indirect effects of happiness on income, whereas γ_3 and $(\gamma_1\phi_2)$ are the direct and indirect effects of poor health, and γ_4 and $(\gamma_1\phi_3)$ are the direct and indirect effects of being female on income.

From equation (3), we obtain the combined residual term φ_{it} (= s_i +ε_{it}) but not the separate estimates of s_i and ε_{it}. However, given φ_{it} , $\sigma^2_{s_i}$ and $\sigma^2_{\varepsilon_{it}}$ one can obtain the minimum variance estimate of s_i as (King and Dicks-Mireaux, 1982, p 252):

$$\tilde{s}_i = \lambda(\overline{\varphi}_i) \tag{6}$$

where $\lambda = \sigma^2_{s_i} / (\sigma^2_{s_i} + \sigma^2_{\varepsilon_{it}})$ and $\overline{\varphi}_i$ is the combined residual term averaged over the time periods. Then, $\tilde{\varepsilon}_{it} = \hat{\varphi}_{it} - \tilde{s}_i$.

For expositional ease, equation (5) may be rewritten as

$$Y_{it} = \sum_k b_k Z_{kit} = Z_{it} b \tag{7}$$

where

Z_{it} = [1 H_{it} H_{it} V_{1it} V_{2it} V_{3it} OW_{it} $Graduate_{it}$ P_{it} P_{it} $Female_i$ $Female_i$ $City_{it}$ $Professional_{it}$ $White\ collar_{it}$ $Blue\ collar_{it}$ $Others_{it}$ $\tilde{s}_i$ $\tilde{\varepsilon}_{it}$] and

$$b' = [\gamma_0\ \ \beta\ \ \gamma_1\phi_1\ \ \alpha_1\ \ \alpha_2\ \ \alpha_3\ \ \gamma_1\ \ \gamma_2\ \ \gamma_3\ \ \gamma_1\phi_2\ \ \gamma_4\ \ \gamma_1\phi_3\ \ \gamma_5\ \ \gamma_6\ \ \gamma_7\ \ \gamma_8\ \ \gamma_9\ \ 1\ \ 1]\ .$$

The term (b_k Z_{kit}) represents the income flow from the k-th variable. The income flow from age will be represented by ($\alpha_1 V_{1it}$ + $\alpha_2 V_{2it}$ + $\alpha_3 V_{3it}$) and that from occupational factors by (γ_0 + γ_6 $Professional_{it}$ + γ_7 $White\ collar_{it}$ + γ_8 $Blue\ collar_{it}$ + γ_9 $Others_{it}$). Since there is no interaction term in our income generating model, the income flows serve as mutually exclusive components.

2.2 Decomposition of Inequality by Income Flows: The Choice of Decomposition Rules

Let $Y = (Y_1, Y_2, \ldots, Y_n)$ represent the distribution vector of incomes among n individuals. Then, a measure of inequality, say I, can be written as the weighted sum of incomes (time script t is suppressed throughout this sub-section).

$$I = \sum_i w_i(Y, I) Y_i \tag{8}$$

where $w_i (Y, I)$ is the distributional weight associated with Y_i. Substituting $\sum b_k Z_{ki}$ for Y_i, we have

$$I = \sum_k \sum_i w_i(Y, I) b_k Z_{ki} . \tag{9}$$

This is known as the natural decomposition of income inequality (Shorrocks, 1982). The contribution of the k-th variable to income inequality is represented by

$$v_k(I) = \sum_i w_i(Y, I) b_k Z_{ki} . \tag{10}$$

This, when expressed as a proportion of total inequality, is called the decomposition rule for inequality measure I.

$$\tilde{v}_k(I) = v_k(I) / I . \tag{11}$$

All inequality measures, except the Atkinson indices, are decomposable as in (9). The decomposition of Gini coefficient was first proposed in Fei et al. (1978) and later elaborated on and extended in Pyatt et al. (1980) and Lerman and Yitzhaki (1985). Paul (2004) provided decomposition rules for the entire class of entropy measures.

Since inequality measures differ in terms of distributional weights, their decomposition rules differ from each other. To get a decomposition rule (equation) independent of the functional forms of inequality measures, Shorrocks (1982) imposed certain stringent constraints on the decomposition procedure and arrived at a unique decomposition rule which turned out to be the decomposition equation for variance. This so-called unique decomposition rule is based on the requirement that a given income source makes no contribution to aggregate inequality if every individual receives equal income from that source. This requirement is untenable because if each person receives a constant positive income from a source, then inequality declines. That is, a decomposition rule must assign a negative inequality contribution to any source income that is equally distributed and is positive. This condition is called the property of '*negativity*' in Paul (2004)[13] and is satisfied if the sum of distributional weights is less than zero, i.e. $\sum_i w_i(Y, I) < 0$.

As shown in Paul (2004, p. 441), only a sub-class of the entropy measures with inequality aversion parameter 0 < c < 2 (which includes Theil's T_1) meets the *negativity* requirement and hence can be used for assigning inequality contributions to income sources unambiguously. The Gini index and the generalized entropy indices for c ≤ 0 and c ≥ 2 (which include half of the squared coefficient of variation and Theil's T_0) fail to satisfy this test and thus are unsuitable for decomposing inequality. For our empirical analysis, we hence rely on the decomposition rules of entropy measures for c = 1 and 1.1 which satisfy the *negativity* requirement[14]. The generalized entropy indices are specified as

$$\begin{aligned} T_c &= \{1/nc(c-1)\}\sum_i \{(Y_i/\mu)^c - 1\} \qquad \text{for } c \neq 0, 1 \\ &= \sum_i w_i(Y;T_c)Y_i = \sum_k \sum_i w_i(Y, T_c)\, b_k Z_{ki} = \sum_k v_k(T_c) \end{aligned} \tag{12}$$

where $w_i(Y, T_c) = [1/\{nc(c-1)\mu^c\}](Y_i^{c-1} - \mu^{c-1})$ is the distributional weight and μ the mean income. The decomposition rule is expressed as

$$\tilde{v}_k(T_c) = v_k(T_c)/T_c = \frac{\sum_i (Y_i^{c-1} - \mu^{c-1})\, b_k Z_{ki}}{\sum_i (Y_i^{c-1} - \mu^{c-1})Y_i} \qquad \text{for } c \neq 0, 1 \tag{13}$$

For c = 1

$$\begin{aligned} T_1 &= \frac{1}{n}\sum_i (Y_i/\mu)\ln(Y_i/\mu) \\ &= \sum_i w_i(Y, T_1)Y_i = \sum_k \sum_i w_i(Y, T_1)\, b_k Z_{ki} = \sum_k v_k(T_1) \end{aligned} \tag{14}$$

where $w_i(Y, T_1) = (1/n\mu)\ln(Y_i/\mu)$ is the distributional weight. The decomposition rule for this index is given by

$$\tilde{v}_k(T_1) = v_k(T_1)/T_1 = \frac{\sum_i (\ln Y_i - \ln \mu)\, b_k Z_{ki}}{\sum_i (\ln Y_i - \ln \mu)Y_i}. \tag{15}$$

[13] Morduch and Sicular (2002) call this the property of '*equal additions*'.
[14] The use of decomposition rules of these two entropy measures also enable us to see the sensitivity of results.

3. Data and Variables

The panel data from the first 14 Waves (2001 to 2014) of the HILDA surveys are used to examine the effects of happiness on income generation and inequality. The variables used in the estimation of models (3) and (4) are defined as follows. Happiness (life satisfaction) is measured on a scale numbered from 0 to 10 according to each person's response to the following question: "All things considered, how satisfied are you with your life?" Individual income is defined as financial year disposable income. All incomes are converted into constant 2014 prices using consumer price indices available from the Australian Bureau of Statistics. To prevent zero income values from being treated as missing data, $1 is added to all incomes. An added advantage of this is that it facilitated the computation of Theil's entropy measures which require log values of income.

In the HILDA surveys, work-hours of an individual are recorded as 'hours per week usually worked in all jobs' in the survey year, and age is measured in years. Binary variables are generated for females, graduates (university degree holders), those who suffer from poor health, and those who live within a major city. People are labelled as suffering from poor health if they have a long-term health condition. For occupational status, dummy variables are used for professionals, white collars, blue collars, and others (managers serve as the reference group). The correlation matrix of these variables presented in Appendix Table A2 shows no evidence of multicollinearity.

The summary statistics presented in Table 1 reveal that the mean income (Aus$ at 2014 prices) of individuals increased from $40,833 in Wave 1 to $50,582 in Wave 14, reflecting an increase of 24 per cent over the entire period. Income inequality measured in terms of entropy measures ($T_{c=1}$ and $T_{c=1.1}$) declined during this period. The number of university graduates increased by 7.3 percentage points, while the number of individuals with poor health increased by 2.4 percentage points. The average work-hours per week declined only marginally over the years. The average self-reported life satisfaction (happiness) score has remained constant. The distribution of life satisfaction scores is negatively skewed. As can be seen from Appendix Table A3, only 3 per cent of individuals report a life satisfaction score of ≤ 4. A large proportion of individuals report happiness scores in the range of 7-10 each year.

4. Empirical Results

Tables 2 and 3 present the Hausman-Taylor estimates of the income generating function (3) and work-hours equation (4) respectively. All the estimated coefficients seem to be reasonable in terms of their signs and magnitude and most of them are statistically different from zero at 1% level of significance. The coefficient of happiness in the income generating equation is positive (β = 330.77) which suggests that happiness directly augments the performance of an individual in earning activities. We may note that happiness has two constituent elements. The first element consists of positive character traits such as smiling, optimism and self-discipline, and the second element consists of negative (bad) character traits such as stress and pessimism. It is first element that improves the productive efficiency of an individual.

The positive coefficient of work hours implies that an additional work hour per week adds \$282.86 to the yearly income of an individual. Since happiness has a negative effect on work hours (ϕ_1 = -0.41), the indirect effect of a 1-point rise in happiness on income is negative ($\gamma_1\phi_1$ = -115.97). This is the opportunity cost of leisure an individual is willing to incur as she moves one point upward on the life satisfaction (happiness) scale.

The direct effect of happiness on income is stronger than its indirect effect. Hence, the net effect of a 1-point rise in life satisfaction on yearly income is positive, \$214.8 = \$330.77 – \$115.97. This means that, other things remaining the same, an individual who is 'totally satisfied' with life earns \$2,148 more than an individual who is 'totally unsatisfied' with life.

The elasticity of income (η) with respect to a 1-point increase in happiness calculated at the 2014 mean income is 0.42 [$\eta = (100/\bar{Y})\partial Y/\partial H$ = (100/50,582) (330.77-115.97)] which is the sum of the direct (0.65) and indirect (-0.23) elasticity estimates. This suggests that a 1-point increase in happiness leads to a 0.42 per cent increase in income. This elasticity is much lower than the one (3 per cent) reported in Graham et al. (2004) for Russia. Note that the Russian study relates to an extraordinarily complex and unstable time. In a very unstable context, where the rewards for all different skill sets are changing, one can imagine that a positive attitude matters more than in a stable context like Australia[15].

The coefficients of V_1 and V_2 in equation (3) are positive but the coefficient of the latter is lower than the former. This indicates that the rate of change in income decelerates for the age group, 25–35. Since the coefficient of V_3 is negative and significant, a hump-shaped pattern for the age-income profile is observed. Poor health adversely affects productive efficiency, leading to a decline in income of \$563.47 per year. Individuals with poor health work 1.16 fewer hours each week, compared to those who are healthy (Table 3). Thus, the indirect effect of poor health on income (through a reduction in working hours) is also negative ($\gamma_1\phi_2$ = -264.28). Summing these direct and indirect effects, we can say that each year, *ceteris paribus*, an individual with poor health earns \$927.75 less than an individual who is healthy. Based on their direct and indirect effects, females are found to earn about \$12404.69 (=10,008.39+2396.30) less than males. University degree holders earn \$7,973 more than those who do not have a university degree. Those who live in big cities earn about \$3,523 more than those who live in smaller cities. This is understandable since big cities provide greater earning opportunities. There are also significant differences in income between occupations, with managers (default) at the top and blue collars at the lower end.

We now turn to the decomposition of inequality by income flows from different variables. Since contributions of happiness and other variables to inequality may not change on a year to year basis, we present inequality decomposition results only for selective years -

[15] The observed difference in elasticity estimates could also have arisen due to differences in the definition of happiness and methodology used. In the Russian study, happiness is measured on a scale from 1 to 5, whereas a scale from 1 to 10 is used in Australia. This suggests that the income elasticity of a 1-point increase in happiness in Australia should be compared with the income elasticity of a 4/10-point increase in happiness in Russia, which turns out to be η = 3.0 x 4/10 = 1.2. This is still higher than the one obtained for Australia. To check whether methodology matters, the Graham et al. (2004) approach is applied to our data set. That is, we first regressed happiness on income and all other conventional variables using the 2001 data and obtained estimates of residual happiness. Then, we regressed income in 2005 on the 2001 residual happiness and all other variables used in model (3). The coefficient of residual happiness turned out to be 195.415 and statistically significant at 8 per cent. This provided us an income elasticity of 0.72 with respect to a 1-point increase in residual income. This estimate is still lower that the one observed for Russia (1.2) based on a comparable happiness scale. This reconfirms our belief that in an unstable context, happiness matters more than in a very stable context like Australia.

2001, 2005, 2010 and 2014. Table 4 presents the decomposition results based on the entropy rule $\tilde{v}_k(T_{c=1.0})$. We observe that during 2001 happiness reduced income inequality by 12.83 per cent through its direct (efficiency) effect but enhanced it by 4.5 per cent through its indirect effect (via a reduction in work hours). Thus, happiness leads to an 8.33 per cent net reduction in income inequality. Happiness is also seen to be playing a similar role in reducing inequality in the subsequent years.

The inequality reducing role of happiness is understandable since the elasticity of income (η) with respect to a 1-point rise in happiness is quite large at the low-income levels and small at the higher income levels. For instance, estimates of η are 2.15, 1.43, 1.07, 0.61 and 0.53 respectively at income levels of $10,000, $15,000, $20,000, $35,000, and $40,000. Thus, in terms of percentages, the benefit of happiness in improving one's income generating capacity is stronger for those at lower levels of income and weaker for those individuals at higher levels of income. It is for this reason that the happiness-induced income shares in aggregate income decline as we move on to higher quintile groups (Table 5). Graham et al. (2004, p. 332) make a similar observation for Russia: "In comparison to those respondents in the lowest quintiles, happiness matters less to future income for those in wealthier quintiles, although the difference is just short of significant." These disproportionate effects on income seem plausible as the positive character traits of happiness matter more to lower income individuals who are likely to be judged by their attitudes and efforts than by their skills, as higher earning workers are.

Other variables that are found to reduce inequality are age, living in a big city, being a graduate, and obligatory work-hours. The inequality reducing role of big cities seems to have diminished over the years. Poor health contributed 2.75 per cent to income inequality during 2001. This is to our expectation as poor health causes a greater percentage reduction in income in the lower quintiles as compared to the upper quintiles (Table 5). We further note that the direct effect of poor health on income inequality is stronger than its indirect effect. Both these effects have a mild tendency to decline over time, which is consistent with the declining incidence of poor health after 2005 (Table 1). Other variables that are found to enhance inequality are sex, occupational structure, and individual-specific and general random factors. These results are consistent with the fact that each of these variables causes a greater reduction in income in the lower quintiles as compared to the upper quintiles (Table 5).

To see the sensitivity of results, the inequality contributions are also obtained based on entropy decomposition rule, $\tilde{v}_k(T_{c=1.1})$. These results are presented in Appendix Table A4. The results are quite similar to those discussed above, though a few of them are somewhat different in quantitative terms. Nonetheless, our main conclusions remain intact.

5. Concluding Remarks

This is the first study to examine the effect of happiness on income inequality by exploring the causality from happiness to income. We posited that happiness impacts upon the income generating capacity of individuals directly by inducing efficiency in earning activities and indirectly by affecting their time allocation for paid work. Both these effects of happiness on income generation are tested in a model consisting of an income generating function and a work-hour equation. The model is estimated using the panel survey data for Australia.

The direct effect of happiness on income is positive but its indirect income effect via reduction in work hours is negative. The indirect effect suggests that happy individuals prefer to enjoy more leisure time than others. Since the direct effect is stronger than the indirect effect, the net effect of happiness on income generation is positive and significant. Other things remaining the same, an individual who is ‘totally satisfied’ with life earns $2,148 more each year than an individual who is ‘totally unsatisfied’ with life. The elasticity of income with respect to a 1-point increase in happiness, calculated at the 2014 mean income, is 0.42.

The relative contributions of happiness and other variables to income inequality are obtained by inserting their income inflows into entropy decomposition equations. Happiness matters more to those individuals at lower levels of income and less to those at higher levels of income. This is reflected in the declining income elasticity of happiness with the level of income. These disproportionate effects of happiness lead to a reduction in income inequality.

The research presented in this paper can be extended and improved along the following lines. While the theory of disproportionate effects of happiness seems plausible, further insights can be gained by considering the 'mediating role' of individual personality traits such as cheerfulness, optimism, and self-esteem along with other variables in the income generating equation[16]. Second, the quintile regressions can also be used to test the happiness advantage to low-income earners.

Third, attrition in the data set can be an issue, especially in longer time series. The present study has ignored this issue as well as the possible weighting. The issue needs to be investigated to rule out the possibility that the relationship is not driven by self-selection of those who remained in the sample. This issue is a reasonable topic for further research.

Finally, it would be of interest to see whether the results reported here generalize to other countries and data sets. The relationship between happiness and income inequality is likely to vary depending on the country context (e.g. whether it is wealthy, stable, in an unstable transition etc.), and depending on the distribution of happiness in the country. The happiness distribution in Australia is skewed (i.e. there are very few unhappy people), but again how this would work in a country with lower levels of average happiness, as well as income, remains an open question.

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[16] This route could not be explored here due to non-availability of data on individual traits.

Table 1: Summary Statistics for the Sample Period 2001-2014 and Selected Years

Variables	2001-2014 (Wave 1 to Wave 14)	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
Mean Income (Aus$ at 2014 prices)	46,858	40,833	43,328	49,856	50,582
Age (Years)	44.24	43.63	44.08	44.07	44.77
Average Happiness (Scores)	7.9	8.0	7.8	7.9	7.9
Work Hours (Average work hours per week)	36.7	37.6	36.8	36.4	36.0
Graduates (%)	26.9	23.5	26.0	26.8	30.8
Females (%)	47.7	46.8	47.8	50.0	42.2
City (Individuals living in major cities) (%)	67.1	65.6	66.3	66.8	69.3
Individuals in Poor Health (%)	16.06	14.0	17.3	16.4	16.4
Occupational Distribution (%) Manager	13.2	13.6	12.7	12.7	14.0
Professional	23.2	22.4	22.8	23.4	24.2
White collar	14.7	14.9	15.6	14.8	13.4
Blue collar	29.2	31.2	29.2	29.0	28.1
Other Occupations	19.7	17.9	19.7	20.1	20.3
Entropy Income Inequality Measures $T_{c=1}$		0.2726	0.2595	0.2765	0.2309
$T_{c=1.1}$		0.2708	0.2582	0.2652	0.2238
Number of observations	126258	8461	8209	8603	10895

Source: Author’s calculations

Table 2: Hausman-Taylor Estimates of the Income Generating Function

Explanatory Variable	Coefficient	Value	Robust Standard Error
Happiness	β	330.77	86.76
V_1	α_1	3510.98	61.63
V_2	α_2	1227.60	45.29
V_3	α_3	-16.54	2.28
Work Hours (W)	γ_1	282.86	10.81
Graduate	γ_2	7973.17	461.63
Poor Health (P)	γ_3	-563.47	292.48
Female	γ_4	-10008.39	429.28
City	γ_5	3523.03	409.93
Professional	γ_6	-1237.97	603.90
White collar	γ_7	-3020.38	494.98
Blue collar	γ_8	-4056.40	468.61
Other Occupations	γ_9	-3600.86	493.92
Constant	γ_0	-11623.13	1060.15

The coefficients of Poor Health and Professionals are significant at 5% and all other coefficients are significant at 1% level.

$\sigma_s = 43810.64$

$\sigma_\varepsilon = 25329.62$

λ (fraction of variance due to s) = 0.75

Wald Test: $\chi^2(13) = 13753.03$

Number of observations = 126,258

Time varying exogenous variables: V_1, V_2, V_3, Graduate, City, Poor Health, Professional, White collar, Blue collar, and Other Occupations.

Time varying endogenous variables: Happiness, and Work Hours

Time-invariant exogenous variable: Female

Table 3: Hausman-Taylor Estimates of the Work Hours Equation

Explanatory Variable	Coefficient	Value	Robust Standard Error
Happiness	ϕ_1	-0.4100	0.0422
Poor Health (P)	ϕ_2	-1.1636	0.1240
Female	ϕ_3	-8.4717	0.1884
Constant	ϕ_0	42.2809	0.3619

All the coefficients are significant at 1% level

$\sigma_\eta = 16.20$

$\sigma_e = 9.89$

λ (fraction of variance due to η) = 0.73

Wald Test: $\chi^2(3) = 1377.95$

Number of observations = 126,889

Time varying exogenous variables: Poor Health.

Time varying endogenous variables: Happiness

Time-invariant exogenous variable: Females

Table 4: Percentage Contributions of Explanatory Variables to Income Inequality based on Entropy Decomposition Rule, $\tilde{v}_k(T_{c=1})$

Contributory Factors	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
Age	-149.76	-112.44	-104.25	-88.07
Happiness: Direct	-12.83	-11.14	-9.65	-8.03
Happiness: Indirect	4.50	3.90	3.38	2.82
Graduate	-1.49	-0.81	-1.16	-1.29
Female: Direct	31.85	28.04	23.44	20.13
Female: Indirect	7.62	6.71	5.61	4.82
City	-10.18	-8.94	-7.68	-6.44
Poor Health: Direct	0.43	0.47	0.32	0.30
Poor Health: Indirect	0.25	0.28	0.19	0.17
Occupational Structure	72.47	63.93	54.63	45.33
Obligatory Work Hours	-43.05	-35.74	-31.14	-23.69
Individual Random Effects	93.48	70.67	52.16	44.51
General Random Effects	106.70	95.09	114.17	109.42
Total	100	100	100	100
Entropy Inequality Indices ($T_{c=1}$)	0.2726	0.2595	0.2765	0.2309

Table 5: Percentage Contributions of Explanatory Variables to Income in Different Quintile Groups

Income Quintiles	Age	Happiness	Happiness-Induced Work loss	Graduate	Female	Female Work Effect	City	Poor Health	Poor Health-Induced Work Loss	Occupa-tional Structure	Obligatory Work Hours	Individual Random Effects	General Random Effects
2001 (Wave 1)													
1	577.44	41.20	-14.45	16.97	-89.34	-21.39	33.49	-1.33	-0.78	-227.14	156.95	-154.33	-217.29
2	182.75	10.41	-3.65	4.19	-24.02	-5.75	8.18	-0.36	-0.21	-57.60	45.84	-45.47	-14.24
3	131.66	6.93	-2.43	3.79	-13.29	-3.18	6.06	-0.20	-0.11	-38.64	35.02	-21.88	-3.74
4	102.00	5.12	-1.79	4.39	-8.12	-1.95	4.86	-0.14	-0.08	-27.72	27.74	-5.61	1.30
5	65.04	3.12	-1.10	4.23	-2.93	-0.70	3.08	-0.09	-0.05	-16.06	17.40	20.16	7.88
All	211.78	13.36	-4.68	6.72	-27.54	-6.59	11.13	-0.42	-0.25	-73.43	56.59	-41.43	-45.22
2005 (Wave 5)													
1	427.64	32.95	-11.55	13.39	-73.17	-17.52	28.45	-1.29	-0.75	-184.42	121.69	-73.55	-161.88
2	168.96	9.61	-3.37	5.07	-22.57	-5.40	8.07	-0.44	-0.25	-54.08	41.80	-35.92	-11.48
3	125.23	6.47	-2.27	4.05	-12.63	-3.02	5.69	-0.24	-0.14	-36.51	33.21	-17.13	-2.72
4	97.96	4.80	-1.68	4.83	-8.02	-1.92	4.58	-0.16	-0.09	-26.34	26.06	-2.63	2.62
5	62.46	2.95	-1.04	4.23	-3.04	-0.73	2.86	-0.10	-0.06	-15.20	16.39	22.84	8.43
All	176.45	11.36	-3.98	6.31	-23.89	-5.72	9.93	-0.44	-0.26	-63.31	47.83	-21.28	-33.01
2010 (Wave 10)													
1	382.66	29.48	-10.34	13.59	-64.64	-15.48	24.95	-1.00	-0.58	-162.65	106.63	-34.37	-168.26
2	150.61	8.42	-2.95	4.03	-19.34	-4.63	7.03	-0.39	-0.23	-47.78	36.92	-22.89	-8.81
3	111.16	5.74	-2.01	3.40	-10.99	-2.63	5.27	-0.22	-0.13	-32.29	28.78	-7.93	1.86
4	87.81	4.34	-1.52	4.59	-7.44	-1.78	4.04	-0.13	-0.08	-23.54	22.91	3.71	7.08
5	53.07	2.49	-0.87	3.76	-2.72	-0.65	2.45	-0.07	-0.04	-12.75	13.79	21.41	20.13
All	157.06	10.09	-3.54	5.87	-21.02	-5.03	8.75	-0.36	-0.21	-55.80	41.81	-8.01	-29.60
2014 (Wave 14)													
1	363.97	26.69	-9.36	16.25	-55.65	-13.32	23.52	-0.99	-0.58	-146.43	93.95	-37.34	-160.61
2	150.29	8.33	-2.92	5.32	-19.37	-4.64	7.51	-0.34	-0.20	-46.80	35.48	-19.03	-13.63

3	110.77	5.79	-2.03	4.29	-11.70	-2.80	5.26	-0.21	-0.12	-31.83	28.31	-4.36	-1.37
4	87.48	4.29	-1.50	4.87	-7.38	-1.77	4.13	-0.14	-0.08	-23.07	22.70	4.57	5.91
5	53.10	2.49	-0.87	3.86	-2.58	-0.62	2.48	-0.07	-0.04	-12.62	13.69	22.04	19.14
All	153.12	9.52	-3.34	6.92	-19.34	-4.63	8.58	-0.35	-0.20	-52.15	38.83	-6.83	-30.11

Appendix Table A1: Within-Variation of Time Varying Explanatory Variables

Variable		Mean	Std. Dev.	Min	Max
V_1	Overall	9.11	2.19	0	10
	Between		2.56	0	10
	Within		1.02	1.41	15.78
V_2	Overall	15.04	12.50	0	64
	Between		12.80	0	61.50
	Within		2.96	5.84	24.24
V_3	Overall	155.12	264.24	0	2916
	Between		262.96	0	26.5
	Within		80.02	-451.37	894.80
Happiness	Overall	7.89	1.34	0	10
	Between		1.21	0	10
	Within		0.86	-4.32	14.89
Work Hours	Overall	36.62	15.64	0	150
	Between		14.45	0	150
	Within		9.01	-37.09	145.24
Graduate	Overall	0.27	0.44	0	1
	Between		0.41	0	1
	Within		0.11	-0.65	1.20
Poor Health	Overall	0.16	0.36	0	1
	Between		0.30	0	1
	Within		0.26	-0.76	1.09
City	Overall	0.67	0.47	0	1
	Between		0.45	0	1
	Within		0.15	-0.26	1.60
Professional	Overall	0.23	0.42	0	1
	Between		0.35	0	1
	Within		0.26	-0.70	1.16
White collar	Overall	0.15	0.35	0	1
	Between		0.30	0	1
	Within		0.21	-0.78	1.08
Blue collar	Overall	0.29	0.45	0	1
	Between		0.42	0	1
	Within		0.22	-0.64	1.22
Other Occupations	Overall	0.20	0.40	0	1
	Between		0.37	0	1
	Within		0.23	-0.73	1.13

Note: These estimates are obtained by using the command *xtsum* in STATA.

Appendix Table A2: Correlation Matrix of Explanatory Variables

	V_1	V_2	V_3	Happiness	Graduate	Female	City	Work Hours	Poor Health	Professi-onal	White collar	Blue collar	Other Occupations
V_1	1												
V_2	0.4885	1											
V_3	0.2381	0.8474	1										
Happiness	-0.0861	0.0083	0.0688	1									
Graduate	0.2096	0.0574	0.0028	-0.0218	1								
Female	-0.0294	-0.0247	-0.0369	0.017	0.0749	1							
City	0.0149	-0.0636	-0.0644	-0.0538	0.1457	0.0095	1						
Work Hours	0.3189	0.0708	-0.0439	-0.0705	0.075	-0.3385	-0.0149	1					
Poor Health	0.0707	0.1692	0.1674	-0.1111	-0.0373	-0.0014	-0.0336	-0.0434	1				
Professional	0.1718	0.0664	0.0296	-0.0068	0.5374	0.0805	0.1033	0.0481	-0.0198	1			
White collar	0.0636	0.0367	0.0113	-0.0048	-0.0986	0.2292	0.0586	-0.0839	-0.002	-0.2277	1		
Blue collar	-0.0687	-0.0528	-0.0298	-0.0075	-0.3108	-0.3503	-0.1047	0.0694	0.0217	-0.3522	-0.2662	1	
Other Occupations	-0.272	-0.1562	-0.0927	0.0149	-0.1821	0.1998	-0.0116	-0.2647	-0.0079	-0.271	-0.2048	-0.3169	1

Appendix Table A3: Distribution of Individuals by Life Satisfaction Scores (Percentages)

Life Satisfaction Scores	2001 -2014 (Wave 1-Wave 14)	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
0	0.2	0.2	0.1	0.1	0.0
1	0.2	0.1	0.1	0.1	0.0
2	0.4	0.5	0.2	0.1	0.1
3	0.7	0.5	0.5	0.4	0.3
4	1.2	1.0	0.9	0.8	0.9
5	4.2	4.4	3.9	3.0	2.8
6	5.9	6.3	6.5	5.8	5.4
7	19.0	19.5	21.4	22.5	21.1
8	33.5	32.3	36.1	37.5	37.7
9	21.7	20.2	21.1	21.3	22.9
10	13.0	15.0	9.1	8.4	8.8
Average Score	7.9	8.0	7.8	7.9	7.9

Source: Author’s calculations

Appendix Table A4: Percentage Contributions of Explanatory Variables to Income Inequality based on Entropy Decomposition Rule, $\tilde{v}_k(T_{c=1.1})$

Contributory Factors	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
Age	-101.52	-75.95	-69.40	-60.49
Happiness: Direct	-8.92	-7.87	-6.74	-5.70
Happiness: Indirect	3.13	2.76	2.36	2.00
Graduate	-0.17	-0.23	-0.02	-0.31
Female: Direct	23.56	21.12	17.58	15.02
Female: Indirect	5.64	5.06	4.21	3.60
City	-6.80	-6.23	-5.26	-4.46
Poor Health: Direct	0.31	0.34	0.24	0.22
Poor Health: Indirect	0.18	0.20	0.14	0.13
Occupational Structure	50.72	45.67	38.48	32.49
Obligatory Work Hours	-28.56	-23.87	-20.56	-15.80
Individual Random Effects	79.89	64.41	46.68	41.94
General Random Effects	82.52	74.15	92.27	91.35
Total	100	100	100	100
Entropy Inequality Indices ($T_{c=1.1}$)	0.2708	0.2582	0.2652	0.2238

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