Reversing the Causality- Does Happiness Reduce Income Inequality?

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Abstract

This paper investigates the effect of happiness (self reported life satisfaction) on income inequality by exploring the causality from happiness to income based on the panel data from the first five waves (2001-2005) of Household Income and Labour Dynamics in Australia (HILDA) survey. Happiness is hypothesized to impact upon the income generating capacity of an individual directly by stimulating working efficiency and indirectly through its effect on the 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 work hour equation. The income flows of happiness and other variables obtained from the model are inserted into the income inequality decomposition equations to obtain their relative inequality contributions. The empirical results reveal that happiness has a positive effect on income generation and contributes to the reduction of inequality.

Keywords: Happiness, income generating function, work hours, inequality decomposition

1. **Introduction**

The happiness or life satisfaction studies are getting increasingly more attention among economists, psychologists and policy makers. The first prominent study of happiness was undertaken by Easterlin (1974) to investigate whether economic growth has any positive impact on happiness in the United States. He noted that while at a point of time richer are happier, overtime income growth does not raise happiness. This apparent inconsistency between these two phenomenons is now known as the Easterlin paradox. The effect of income on happiness in the subsequent studies of other developed economies varies from positive to insignificant or even negative. There are other related contributions on the effects on happiness of unemployment, inflation and income inequality, see, e.g. Clark and Oswald (1994), Di Tella et al (2001) and Alesina et.al. (2004). Ferrer-i-Carbonell and

Frijters (2004) and Clark et al (2008) have provided excellent reviews of happiness literature.

In this paper, we explore the possibility of a reverse causation, i.e., happiness may lead to higher income/earning. Economist and other social scientists know very little of the mechanism through which happiness affects human performance. However, there is a vast literature in psychology revealing that workers who experience positive emotions (a term used to reflect happiness) show less emotional exhaustion and low absenteeism at work (Iverson et al , 1998; Wright and Cropanzano, 1998; George, 1989; Gil et al, 2004). The happy people have higher self-esteem and are more disciplined in their actions (Guven, 2007; Frank, 1997 and Kenny, 1999). Amabile et al (2005) provide some evidence that happiness incites greater creativity.

In an interesting experimental study, Oswald et al (2008) designed a randomized trial at the University of Warwick to see how emotions affect human productivity. They ran the experiment twice, both times working with 182 subjects. The first time, they induced happiness in a group of people by showing them 10 minutes of comedy clips. Another group saw no clips. Then, both groups took a short math test. They were told they would be paid based on how many questions they answered correctly. The group that had watched the clips answered 10% more questions correctly than the group that hadn't.

The link between good emotions (feeling of happiness) and work performance is also evident across diverse work environments. For instance, happy cricket players show superior performance during games (Totterdell, 1999, 2000). 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 contrary, Sanna et al (1996) suggest that individuals in negative mood put forth the most effort. This is consistent with the generally held view that academics produce a large and of high quality research output under stress while going for tenure at the North American Universities.

To the best of my knowledge, no previous economics study, with the exception of Graham et al (2004), has used large sample survey data to investigate the effect of happiness on income. The study of Graham at al is based on the panel data for Russia for 1995 and 2000. These researchers first regress happiness on log income and other conventional variables using data for 1995 and obtain residual happiness as the difference between observed happiness and estimated happiness. Then, they regress the log income in 2000 on residual happiness in 1995. The study reports that a one per cent increase in the unexplained (residual) happiness in 1995 yields approximately 3 percent increase in income in 2000. The study provides no explanation why effect of happiness on income occurs after five years.

If happiness has a significant effect on income, then variations in levels of happiness among individuals are likely to affect the level of income inequality. This is an interesting and important issue with which this paper is mainly concerned. More specifically, we first investigate the effect of happiness on income generating capacity of an individual in a regression model and then examine the extent to which income flow from happiness contributes to inequality. An empirical exercise based on panel data from the first five waves (2001 to 2005) of Household Income and Labour Dynamics in Australia (HILDA) surveys is presented. The results reveal that happiness has a positive significant effect on income generation and contributes about 9% to the reduction of inequality.

The paper is structured as follows. Section 2 discusses the analytical framework that we use for exploring the impact of happiness on income inequality. We specify a model that captures the channels through which happiness may affect the income generating capacity of an individual and then discuss the methodology for assigning inequality contributions to income flows associated with happiness and other relevant variables such as age, education, and work hours. Section 3 discusses the data and the empirical results for Australia. Section 4 concludes the study.

2. The Analytical Framework

At least two major issues are involved in investigating the effect of happiness on income inequality. The first issue relates to the exploring of channels through which happiness may affect the income generating capacity of an individual. Given the results of experiments conducted by Andrew Oswald and his team at Warwick University, we hypothesise that happiness directly enhances the performance of an individual in earning activities. We shall call this the *direct* or *productive* effect of happiness on income generation. Happiness may also affect income indirectly via its impact on the time allocation of an individual. An individual allocates her total time between three activities: (i) paid work (ii) maintenance of health (such as sleeping and resting etc) and (iii) consumption of relational goods. An individual works some hours in the week to earn income which she spends for buying conventional and positional consumption goods. Each individual 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. These goods are jointly produced and are known to be beneficial to individuals. People go on holidays to recharge their energy essentially by consuming relational goods. The consumption of relational goods may neutralise or more than neutralise the 'relational bads' (tense). The latter are consumed while interacting with some unpleasant colleagues and customers at work or with unknown persons in the market place. A happy person may prefer to work more hours per week and produce/earn more. Or, alternatively, a happy person may like to enjoy more leisure time to consume relational goods and thus work less hours per week. The resulting income loss is the cost of consuming relational goods (leisure) a happy person may like to incur/ bear. We shall call it the *indirect* effect of happiness on income. Thus, the total effect of happiness on income will depend on the magnitude and signs of both the *direct* and *indirect* effects. They may reinforce or neutralise each other.

A second issue relates to the choice of an appropriate methodology to assign inequality contributions to the income flows from happiness and other income generating variables. A standard procedure is to choose one or more inequality measures and use their decompositions for assigning inequality contributions to income flows from different regression variables. Since the inequality measures differ in terms of their distributional weights, their decomposition rules (equations) differ from each other. Hence, the choice of decomposition equations becomes important for assigning unambiguous inequality contributions to different income flows. We return to this issue latter in this Section.

Another related issue that is equally crucial and requires mention at the very outset relates to the possibility of bidirectional causality between happiness and income which can lead to simultaneous/ endogeneity bias in the coefficient of happiness variable in income generating function. One effective way to resolve this problem is to use an instrument which is correlated with happiness variable but is uncorrelated with the error term. In a recent attempt to examine the effect of happiness on consumption, saving and risk taking behaviour with panel data for Germany and the Netherlands, Guven (2007) overcomes the problem of indogeneity in each regression equation by instrumenting individual happiness with regional sunshine. However, while working with time series data, the lagged value of the variable serves as a natural instrument in the model (Greene, 2003, pp. 78-79).

2. 1 An Income Generating Model

Consider the following income generating function

$$Y_{0it} = \gamma_0 + \alpha H_{it-1} + g(A_{it}) + x_{it}\gamma + s_i + \varepsilon_{it} \qquad (1)$$

where Y_{0it} is the income of individual i during period t. H_{it-1} is one year lagged self-reported overall life satisfaction (happiness) taking values (scores) between zero ('totally dissatisfied' with life) and 1 ('totally satisfied' with life) as reported in HILDA like most western surveys on life satisfaction. These happiness scores are assumed to be the cardinal numbers. One year lagged values of happiness serve as an instrument for happiness to overcome the problem of endogeneity. Paul and Guilbert (2013) have reported statistically insignificant effect of current and lagged incomes on happiness based on the same data set we use here. Hence, we do not confront with any issues related to causality running from income to happiness.

The function $g(A_{it})$ represents the age-income profile. x_{it} is a vector of work hours and dummies for education, gender, location, poor health and occupations. The choice of these variables is dictated largely by the availability of data. s_i is the time invariant individual-specific effect of unobservable variables like skill, drive, luck and taste and is assumed to have zero mean and constant variance σ_s^2. ε_{it} represents the general effect of transitory factors and is also assumed to have zero mean and constant variance σ_ε^2. We also assume that the variance of combined random term ($\varphi_{it} = s_i + \varepsilon_{it}$) is also constant, $\sigma_\varphi^2 = \sigma_s^2 + \sigma_\varepsilon^2$.

The human capital theory suggests a hump-shaped age-income profile, which in often represented by regressing log income (or log wages) on age and age^2 (see e.g. Murphy and Welch, 1992 and Willis, 1986). But since we are interested in decomposing the inequality of income rather than of log income, we approximate age-income hump profile by a piece-wise function of age. 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 age 15 (which is the minimum age we observed in the sample), then the hump-shaped pattern of age-income profile could be specified as

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

where A_{it} is the age of individual i at time 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

$d_{1it} = 1$ 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

$$\begin{aligned} Y_{0it} &= \gamma_0 + \alpha\, H_{it-1} + \alpha_1 V_{1it} + \alpha_2 V_{2it} + \alpha_3 V_{3it} + \gamma_1 WH_{it} \\ &+ \gamma_2 Graduate_{it} + \gamma_3 PH_{it} + \gamma_4 Female_1 + \gamma_5 City_{it} + \gamma_6\, Professional_{it} \\ &+ \gamma_7 While\ collar_{it} + \gamma_8 Blue\ collar_{it} + \gamma_9 Others_{it} + s_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where Graduate, Poor health (PH), City, Females and four occupations are the dummy variables with Managers as a default category. WH represents the average work hours per week. Given the panel data from waves 1-5 of HILDA, equation (3) can be estimated with generalized least squares (GLS) with random effects.

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 α represents the efficiency (direct) effect of happiness on income generation.

The work hours might be influenced by the level of happiness and poor health of an individual. If this is the case, then both these variables can also indirectly affect the level of income. To explore this, we specify a work hour equation and estimate by GLS random effects. In the absence of any guidance from economic theory, the work hour, for simplicity, is assumed to be a linear function of happiness and poor health.

$$WH_{it} = \phi_0 + \phi_1 H_{it-1} + \phi_2 PH_{it} + \eta_i + e_{it} \tag{4}$$

where η_i and e_{it} are respectively individual time-invariant and general random effects, each is assumed to have zero mean and constant variance. If ϕ_1 and ϕ_2 are statistically significant, then the second and third terms in (4) will represent those portions of work hours that are induced (or constrained) by happiness and poor health respectively. The remaining part $(\phi_0 + \eta_i + e_{it})$ represents what we call here the obligatory work hours (OWH) of a healthy but 'totally unsatisfied' person.

Substituting (4) into (3) we have

$$\begin{aligned} Y_{0it} &= \gamma_0 + (\alpha + \gamma_1\phi_1) H_{it-1} + \alpha_1 V_{1it} + \alpha_2 V_{2it} + \alpha_3 V_{3it} + \gamma_1 \mathrm{OWH}_{it} + \gamma_2 \mathrm{Graduate}_{it} \\ &\quad + (\gamma_3 + \gamma_1\phi_2) PH_{it} + \gamma_4 \mathrm{Female}_1 + \gamma_5 \mathrm{City}_{it} + \gamma_6 \mathrm{Professional}_{it} \\ &\quad + \gamma_7 \mathrm{While\ collar}_{it} + \gamma_8 \mathrm{Blue\ collar}_{it} + \gamma_9 \mathrm{Others}_{it} + s_i + \varepsilon_{it} \end{aligned} \tag{5}$$

Note that α and $(\gamma_1\phi_1)$ are respectively the direct and indirect effects of happiness on income, and γ_3 and $(\gamma_1\phi_2)$ are the direct and indirect effects of poor health on income.

From model (3), one can 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. 254):

$$\hat{s}_i = \lambda(s_i + \varepsilon_{it}) = \lambda(\varphi_{it}) \tag{6}$$

where $\lambda = \sigma^2_{s_i} / (\sigma^2_{s_i} + \sigma^2_{\varepsilon_{it}})$. Since s_i is assumed to be a time invariant individual random effect, we obtain the estimate of s_i by multiplying λ with the combined residual term averaged over the time periods, i.e., we get $\tilde{s}_i = \lambda(\overline{\varphi}_i)$ and then $\tilde{\varepsilon}_{it} = \hat{\varphi}_{it} - \tilde{s}_i$.

For expositional reasons, equation (5) may be rewritten conveniently as

$$Y_{0it} = \sum_{k} Y_{kit} = \sum_{k} b_k Z_{kit} = Z_{it} b \quad (7)$$

where $Y_{kit} = (b_k Z_{kit})$ represent the income flow from the k-th variable.

Z_{it} = [1 H_{it-1} H_{it-1} V_{1it} V_{2it} V_{3it} OWH_{it} $Graduate_{it}$ PH_{it} PH_{it} Female $City_{it}$ $Professional_{it}$ White $collar_{it}$ Blue $collar_{it}$ $Others_{it}$ $\tilde{s}_i$ $\tilde{\varepsilon}_{it}$].

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

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 ($\gamma_0 + \gamma_6$ $Professional_{it}$ + γ_7 White $collar_{it}$ + γ_8 Blue $collar_{it}$ + γ_9 $Others_{it}$)[1].

2.2 Regression based Decomposition of Income Inequality: The Choice of Decomposition Rules

The methodology that forms the basis of our inequality decomposition follows the lead works of Fei, Ranis and Kuo (1978), Pyatt, Chen and Fei (1980), Shorrocks (1982), Lerman and Yitzhaki (1985), Morduch and Secular (2002) and Paul (2004). In this section, we suppress the time subscript t from all the variables for the same of simplicity. If the distribution vector of incomes among n individuals is represented by $Y_0 = (Y_{01}, Y_{02}, \ldots, Y_{0n})$, then a measure of inequality, say I, can be written as the weighted sum of incomes.

$$I = \sum_{i} w_i(Y_0, I) Y_{0i} \quad (8)$$

where $w_i(Y_0, I)$ is the distributional weight associated with Y_{0i}. On substituting $\sum Y_{ki} = \sum b_k Z_{ki}$ for Y_{0i}, we have

$$I = \sum_{k}\sum_{i} w_i(Y_0, I) Y_{ki} = \sum_{k}\sum_{i} w_i(Y_0, I) b_k Z_{ki} \;. \quad (9)$$

This is known as a natural decomposition of income inequality. The replacement of Y_{ki} by bZ_{ki} in (9) maintains the linear structure of decomposition given that income components sum to total income.

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[1] While our methodology (discussed in Section 2.2) allows us to find out the contribution of each individual variable, our interest lies in knowing how age and occupational differences contribute to inequality.

The contribution of the k-th explanatory variable to income inequality is represented by

$$v_k(I) = \sum_i w_i(Y_0, I)Y_{ki} = \sum_i w_i(Y_0, I)b_k Z_{ki} \ . \tag{10}$$

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 measures of inequality, except the Atkinson indices, are decomposable as in (9). The natural decomposition of Gini coefficient proposed by Fei, Ranis and Kuo (1978) and elaborated and extended by Pyatt, Chen and Fei (1980) and Lerman and Yitzhaki (1985) has formed the basis of analysis in most of the earlier studies[2]. Paul (2004) provided decomposition rules for the entire class of entropy measures. Since the inequality measures differ in terms of distributional weights, their decomposition rules differ from each other. The expressions for the decomposition rules of different inequality measures are presented in Table 1.

It is convenient for applied researchers to conduct their research based on a single decomposition rule. In his desire to get a decomposition rule (equation) independent of the functional form of the 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 the aggregate inequality declines. That is, a decomposition rules 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)[3] and is satisfied if the sum of distributional weights is less than zero, i.e. $\sum_i w_i(Y_0, I) < 0$.

[2] See, for example, Stark et al (1986), Paul and Dasgupta (1989), Garner (1993) and Yitzhaki (1992).
[3] Morduch and Secular (2002) have called this the property of '*equal additions*'.

As shown in Paul (2004), 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 $c \leq 0$ and $c \geq 2$ (which include half of the squared coefficient of variation and Theil's T_0) fail to satisfy this test and thus be considered unsuitable for decomposing inequality. For our empirical analysis, we rely on two decompositions rules satisfying the *negativity* requirement, though experiments are also made with unacceptable rules to see their relative performance.

3. An Empirical Illustration with Australian Data

3.1 Data

The panel data for 9300 individuals from the five waves (2001 to 2005) of the Household Income and Labour Dynamics in Australia (HILDA) surveys is used to examine the effects of happiness on income generation and inequality. In these surveys, the respondents are asked detailed questions about economic and subjective wellbeing as well as labour market dynamics. The variables used in the estimation of models (3) and (4) are defined as follows. Happiness (life satisfaction[4]) is measured on a scale numbered from zero to ten according to each person's response to the following question: "All things considered, how satisfied are you with your life?"[5] A score of zero means that the person is completely unsatisfied with life and the score of 10 means that the person is completely satisfied with life. The annual incomes of individuals are converted into constant 2001 prices using consumer price indices available from the Australian Bureau of Statistics (ABS, 2007). To prevent zero income values from being treated as missing data by STATA, \$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.

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[4] We use the terms 'happiness' and 'life satisfaction' interchangeably throughout this paper.

[5] While the validity of self-reported happiness statistics has been a source of considerable debate in recent years, existing empirical studies appear to suggest that there is a lot of important and reliable information contained within these figures, see, e.g., Layard (2005), Gilbert (2006) and Schimmack (2006).

In the HILDA survey, the time spent by an individual in the paid work is recorded as the average work hours per week, and the 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 the occupational status, dummy variables are used for professionals, white collars, blue collars and others (managers serve as the reference group).

Tables 2 through 4 present summary statistics on variables used in estimating equations 3 and 4. The real mean income of individuals increased from $25247 in wave 2 to $27194 in wave 5 showing a growth of 7.7 per cent over the entire period. The rise in income is accompanied by a decline in inequality as revealed by Gini and generalized entropy measures (Table 2). The number of university graduates increased by less than 2 percentage points. The number of individuals with poor health has increased by 10 percentage points. The average work-hours per week show a tendency to increase, though marginally, over the years.

The average self reported life satisfaction (happiness) score has marginally declined or remained constant. The distribution of life satisfaction scores is quite skewed. Only 3 percent 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 (Table 3). This, however, does not mean that individuals have not moved upward or downward on the happiness scale. The mobility statistics presented in Table 4 show that over time about one-third of individuals move downwards on the life satisfaction scale, less than one-third move upwards and all others stay at the same level of life satisfaction.

3.2 Empirical Results

Tables 5 and 6 present the random effect GLS estimates of income generating function (3) and work hours equation (4). R^2 for the income generating function is 0.36, and for the work hours equation 0.09. All the estimated coefficients seem to be reasonable in terms of their signs and magnitude and are statistically different from zero at high levels of significance. In the income generating model, the coefficients of V_1 and V_2 are positive but the coefficient of 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, our data provide a strong support for a hump shaped pattern of age-income profile. The age at which the income level reaches the highest[6] turns out to be 50.

The coefficient of happiness in income generating model is positive (α = 204.18), which suggests that happiness enhances the performance of an individual in earning activities. The positive coefficient of work hours suggests that an additional work hour (per week) adds $195.78 to the income of an individual. Since the happiness has a negative effect on work hours (ϕ_1 = -0.14), the indirect effect on income of one point rise in life satisfaction is negative ($\gamma_1\phi_1$ = -27.41). This is the opportunity cost of leisure an individual is willing to incur as she moves one point upward on life satisfaction scale. Clearly, the direct effect of happiness on income is stronger that the indirect effect. Hence, the net effect on individual's income of one point rise in life satisfaction is positive $176.67 = 204.18 - 27.41. This implies that, other things remaining the same, an individual who is completely satisfied with life earns $1766.7 more than the one who is completely unsatisfied with life.

The elasticity of income with respect to happiness calculated at the 2002 mean levels of income and happiness is 0.056 [$\eta_{Y_0,H} = (\overline{H}/\overline{Y}_0)\partial Y_0/\partial H = (7.9/25247)\ (204.18\ -27.41)$] which is the sum total of the direct (0.064) and indirect (-0.008) elasticity estimates. This suggests that 1 percent increase in happiness leads to 0.056 percent increase in income. This elasticity is much lower than the one (3 per cent) obtained in Graham et al (2004) for Russia. This difference in elasticity estimates between the two countries could be due to differences in model specification, data, and the length of period used for calculating the response. We explore direct and indirect effects of happiness on income generation responses whereas no such distinction is made in Graham et.al. The latter study examines the effect of 1995 residual happiness on income generation in 2000. It should also be noted that the data set used for Russia belongs to a period of drastic social change which might have been reflected in the effects of happiness on income and other variables. The Australian data set relate to a normal period. All these factors should also be kept in mind while comparing our results with those of Graham at al.

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[6] This is worked out by equating (α_2+2α_3 (A_{it}-35)) to zero (first order condition).

Poor health adversely affects the productive efficiency leading to a decline of income by \$793.83 per year. Individuals with poor health work per weeks 3.33 hours less than those who are healthy (Table 6). Thus, the indirect effect of poor health on income (through a reduction in working hours) is also negative ($\gamma_1\phi_2 = -651.95$). Summing these direct and indirect effects, one can say that, other things remaining the same, an individual with poor health earns \$1445.78 less than one who is healthy.

There are other interesting points that emerge from the estimated models. *Cetris peribus*, the university degree holders earn per year \$8408 more than others. Females earn about \$8781 less than males. Those who live in big cities earn about \$2077 more than those who live in smaller cities. Three are 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. Three entropy decomposition rules, namely, $\tilde{v}_k(T_{c=1.0})$, $\tilde{v}_k(T_{c=1.1})$ and $\tilde{v}_k(T_{c=2})$, and the Gini decomposition rule $\tilde{v}_k(G)$ are presented in Table 7. The first two decomposition rules satisfy the '*negativity*' condition, whereas the other two violate this condition. The entropy decomposition rules that satisfy the *negativity* condition provide quite a consistent and plausible picture. During 2002, happiness reduces income inequality (measured by entropy measure, $T_{c=1}$) by 11.24 per cent through its direct (efficiency) effect, but enhances it by 1.52 per cent through its indirect effect (via reduction in work hours). Thus, happiness leads to 9.72 per cent net reduction in income inequality among individuals. This result seems quite sensible in view of the fact that happiness-induced income share in aggregate income declines as we move to higher quintile groups of individuals (see Appendix Table A1)[7]. Happiness is seen to be playing a similar role in reducing inequality in the subsequent years, see Table 7. Other variables that are found to be inequality reducing based on $\tilde{v}_k(T_{c=1.})$ are age, living in big cities and obligatory work hours.

[7] This is consistent with the result for Russia presented in Graham et al (2004,) when these authors report (p.332), "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. In other words, happiness matters to future income to those at lower levels of income."

During 2002, poor health contributes 2.75 per cent to income inequality measured by entropy index $T_{c=1}$. This is quite explicable as poor health causes a greater percentage reduction in income in lower quintiles groups than the upper quintiles (see Appendix Table A1). We further note that the direct effect of poor health on income inequality is stronger than its indirect effect. Both these effects have increased significantly over the years (Table 7) which is consistent with the rising incidence of poor health in Australia (Table 2). Other variables that are found to be inequality enhancing based on the acceptable decomposition rules are graduates, females, occupational structure and individual-specific and general random variables. A similar picture is seen based on the decomposition rule $\tilde{v}_k(T_{c=1.1})$.

The inequality contributions of happiness and other variables based on decomposition rules that violate the *negativity* property are often quite different in magnitude and even opposite in sign in few cases. For example, the entropy decomposition rule $\tilde{v}_k(T_{c=2})$ and Gini decomposition rule $\tilde{v}_k(G)$ reveal that even though the direct contribution of happiness to inequality is negative, it is very low (less than -0.1 %). The indirect contribution of happiness to inequality is revealed almost zero by these decomposition rules. Similarly, the contribution of poor health based on these rules is even less than one-fifth of what acceptable entropy measures have revealed. As opposed to acceptable rules, both $\tilde{v}_k(T_{c=2})$ and $\tilde{v}_k(G)$ assign positive contribution to age which is hard to explain especially when we know that share of age-generated income in the overall income declines as we move to higher quintile groups (Appendix Table A1). Thus, the inequality contributions based on decomposition rules violating *negativity* condition are both unappealing and misleading.

4. Concluding Remarks

This paper has examined the effect of happiness (self reported life satisfaction) on income inequality by exploring the causality from happiness to income based on panel data from the first five waves (2001-2005) of HILDA survey. Happiness is hypothesized to impact upon the income generating capacity of an individual directly by inducing efficiency in earning activities and indirectly through its effect on time allocation for paid work. Both these effects of happiness on income are tested in a model consisting of an income generating function and work hour equation. The income flows of happiness and other variables obtained from the model are inserted into the income inequality decomposition equations (rules) to obtain their relative inequality contributions.

The direct effect of happiness on income is positive but its indirect income effect (via work hours) is negative. Since the direct effect is stronger than the indirect effect, the net effect of happiness on income generation is both positive and significant. Other things remaining the same, an individual who is completely satisfied with life earns in a year \$1766.7 more than the one who is completely unsatisfied with life. The elasticity of income with respect to happiness is 0.056 which is much lower than the one reported in Graham et al (2004) for Russia.

Poor health adversely affects both the productive efficiency and the work hours of an individual, leading to a decline in income. Other things remaining the same, degree holders earn more than others, females earn less than males and those who live in big cities earn more than those who live in small cities. The occupational factors affect income significantly. The data also provide a strong support for a hump shaped pattern of age-income profile. The age at which income reached the highest level turns out to be 50.

The relative inequality contributions of happiness and other variables are obtained by inserting their income inflows into the income inequality decomposition equations (rules). The results based on inequality decomposition rules that satisfy the property of *negativity* are quite sensible and consistent. Happiness does reduce income inequality among individuals. Other variables that are found to be inequality reducing are age, living in big cities and obligatory work hours. Poor health, occupational structure and few other variables are found to be inequality enhancing. The results based on decomposition rules that violate the property of *negativity* are different in magnitude and even opposite in sign in few cases and thus distort the picture.

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Table 1: Decomposition Rules for Gini and Generalized Entropy Measures

<table>
<tr><th>Inequality Measure</th><th>Decomposition rule</th></tr>
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Gini Coefficient

If we arrange the income units in an ascending order ($Y_{01} \le Y_{02} \le ... \le Y_{0n}$), then the Gini coefficient can be written as the weighted sum of incomes.

$$G = \sum_i w_i(Y_0, G)Y_{0i}$$

where $w_i(Y_0, G) = w_i(Y_0; G) = \frac{2}{n^2\mu}\left(i - \frac{n+1}{2}\right)$ is the weight associated with Y_{0i}. μ is mean income. On substituting $\sum Y_{ki}$ for Y_{0i} we have

$$G = \sum_k S_k \sum_i \frac{2}{n^2\mu_k}\left(i - \frac{n+1}{2}\right)Y_{ki} = \sum_k S_k \overline{G}_k$$

where $Y_{ki} = b_k Z_{ki}$ is the regression based income flow from the explanatory variable Z_{ki} . $v_k(G) = S_k\overline{G}_k$. $S_k = (\mu_k / \mu) = (b_k \overline{Z}_k / \mu)$ is the contribution of k-th regression variable to aggregate income. $\overline{G}_k$ is the 'pseudo Gini' which is different from the conventional Gini since the weight attached to Y_{ki} in $\overline{G}_k$ corresponds to the rank of individual i in the distribution of Y_0 which is, in general, not the same as her rank in the distribution of Y_k.

</td><td>

$$\tilde{v}_k(G) = v_k(G)/G = S_k\overline{G}_k / G = \frac{\sum_i \{i-(n+1)/2\}Y_{ki}}{\sum_i \{i-(n+1)/2\}Y_{0i}}$$

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The Generalized Entropy Measures

$T_c = \{1/nc(c-1)\}\sum_i \{(Y_{0i}/\mu)^c - 1\} \qquad c \ne 0, 1$

$$= \sum_i w_i(Y_0; T_c)Y_{0i} = \sum_k\sum_i w_i(Y_0, T_c)Y_{ki} = \sum_k\sum_i w_i(Y_0, T_c)b_k Z_{ki} = \sum_k v_k(T_c)$$

where $w_i(Y_0, T_c) = [1/\{nc(c-1)\mu^c\}](Y_{0i}^{c-1} - \mu^{c-1})$ and c is the inequality aversion parameter.

</td><td>

$$\tilde{v}_k(T_c) = \frac{\sum_i (Y_{0i}^{c-1} - \mu^{c-1})Y_{ki}}{\sum_i (Y_{0i}^{c-1} - \mu^{c-1})Y_{0i}} \qquad c \ne 0, 1$$

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For c = 1:

$$T_1 = \frac{1}{n}\sum_i (Y_{0i}/\mu)\ln(Y_{0i}/\mu)$$

$$= \sum_i w_i(Y_0,T_1)Y_{0i} = \sum_k\sum_i w_i(Y_0,T_1)Y_{ki} = \sum_k\sum_i w_i(Y_0,T_1)b_k Z_{ki} = \sum_k v_k(T_1)$$

where $w_i(Y_0,T_1) = (1/n\mu)\ln(Y_{0i}/\mu)$.

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$$\tilde{v}_k(T_1) = \frac{\sum_i (\ln Y_{0i} - \ln\mu)Y_{ki}}{\sum_i (\ln Y_{0i} - \ln\mu)Y_{0i}}$$

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For c = 0:

$$T_0 = (1/n)\sum_i \ln(\mu/Y_{0i})$$

$$= \sum_i w_i(Y_0,T_0)Y_{0i} = \sum_k\sum_i w_i(Y_0,T_0)Y_{ki} = \sum_k\sum_i w_i(Y_0,T_0)b_k Z_{ki} = \sum_k v_k(T_0)$$

where $w_i(Y_0,T_0) = (1/n)\{(\ln\mu/\mu) - (\ln Y_{0i}/Y_{0i})\}$.

T_1 and T_0 are Theil's first and second entropy measures.

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$$\tilde{v}_k(T_0) = \frac{(\mu_k/\mu)\ln\mu - (1/n)\sum_i \left(Y_{ki}/Y_i\right)\ln Y_{0i}}{\ln\mu - (1/n)\sum_i \ln Y_{0i}}$$

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For c = 2, the generalized entropy reduces to the half of squared coefficient of variation:

$$T_2 = (1/2n\mu^2)\sum_i (Y_{0i} - \mu)Y_{0i}$$

$$= \sum_k\sum_i w_i(Y_0,T_2)Y_{ki} = \sum_k\sum_i w_i(Y_0,T_2)b_k Z_{ki} = \sum v_k(T_2)$$

where $w_i(Y_0,T_2) = (1/2n\mu^2)(Y_{0i} - \mu)$. T_2 is the half of the squared coefficient of variation.

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$\tilde{v}_k(T_2) = \mathrm{Cov}(Y_0,Y_k)/\sigma^2(Y_0)$. This is Shorrocks' so called unique decomposition rule. This is also the decomposition rule of variance. Note that variance is known for even not satisfying the basic desirable properties of an inequality measure.

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Table 2: A Summary Statistics of Data and Variables

Statistics of Interest	2002 (Wave 2)	2003 (Wave 3)	2004 (Wave 4)	2005 (Wave 5)
Mean Real Income (Aus$)	25247	25225	25928	27194
Gini coefficient (G)	0.4288	0.4147	0.4067	0.4029
Generalised Entropy Measures of Inequality				
($T_{c=1}$)	0.3338	0.3083	0.2903	0.2878
($T_{c=1.1}$)	0.3367	0.3108	0.2915	0.2897
($T_{c=2}$)	0.4825	0.4304	0.3714	0.3806
Age (in years)	45.5	46.5	47.5	48.5
Average Happiness(1 year lagged)	8.0	7.9	8.0	7.9
Work Hours (Average work hours per week)	23.4	23.6	23.7	24.0
Graduates (%)	19.8	20.3	21.0	21.5
Female (%)	53.8	53.8	53.8	53.7
City (Individuals living in major cities) (%)	61.4	61.1	60.9	60.6
Individuals in Poor Health (%)	22.1	28.7	27.9	31.0
Occupational Distribution (%)				
Manager	5.6	5.8	6.1	5.7
Professional	23.1	23.1	23.8	24.5
Whitecollar	12.5	12.6	12.5	13.4
Bluecollar	21.3	21.4	20.5	20.5
Other Occupations	37.5	37.0	37.0	36.1

Source: Author's calculations

Table 3: Distribution of Individuals by Life Satisfaction Scores

Happiness Scores	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
0	0.2	0.1	0.2	0.2	0.1
1	0.2	0.1	0.2	0.1	0.2
2	0.5	0.4	0.4	0.4	0.5
3	0.8	0.7	0.7	0.8	0.7
4	1.3	1.4	1.3	1.3	1.2
5	5.1	5.1	3.7	4.1	4.3
6	5.9	5.8	5.7	5.8	6.3
7	16.9	19.2	17.4	18.3	18.8
8	30.0	31.4	32.7	32.7	34.4
9	20.2	20.9	23.3	21.9	21.0
10	19.0	14.8	14.5	14.4	12.5
Average Score	8.0	7.9	8.0	7.9	7.9

Source: Author's calculations

Table 4: Mobility of Happiness (Life Satisfaction)

(Percentage of Individuals)

Period	Rigidity in Happiness (Stayers)	Downward Mobility (Downward Movers)	Upward Mobility (Upward Movers)
2001-2002	38.6	33.4	28.0
2001-2003	37.4	32.0	30.6
2001-2004	37.2	33.0	29.8
2001-2005	35.6	35.8	28.6

Source: Author's calculations. Note that stayers are those whose levels of life satisfaction have not changed from year t to year t+1. The downward (upward) movers are those who have moved downward (upward) on the life satisfaction scale from year t to year t+1.

Table 5: Random Effects GLS Estimates of Income Generation Function

Explanatory variable	Coefficient	Value	Robust Standard Error
Happiness (-1)	α	204.18	55.54
V_1	α_1	1965.98	66.16
V_2	α_2	253.67	23.46
V_3	α_3	-8.67	0.54
Work Hours	γ_1	195.78	11.21
Graduate	γ_2	8408.27	514.55
Poor Health	γ_3	-793.83	233.30
Female	γ_4	-8781.27	360.24
City	γ_5	2076.78	309.55
Professional	γ_6	-2569.90	736.74
Whitecollar	γ_7	-4810.29	782.87
Bluecollar	γ_8	-6384.39	747.97
Other Occupations	γ_9	-5675.60	848.00
Constant	γ_0	5260.38	1036.72

R^2: Within = 0.01
Between = 0.36
Overall = 0.29
σ_s = 15196.65
σ_ε = 12051.99
λ (fraction of variance due to s) = 0.61
No of observations = 37183

Table 6
Random Effects GLS Estimates of Work Hours Equation

Explanatory Variable	Coefficient	Value	Robust Standard Error
Happiness	ϕ_1	-0.14	0.056
Poor Health	ϕ_2	-3.33	0.19
Constant	ϕ_3	25.68	0.50

R^2: Within = 0.001
Between = 0.14
Overall = 0.09
σ_η =18.27
σ_e = 9.57
λ (fraction of variance due to η) = 0.78
Number of observations = 37183

Table 7
Percentage Contributions to Income Inequality: The Decomposition Rules based on Generalised Entropy Indices and Gini coefficient

Contributory Factors	Entropy Decomposition Rules satisfying 'negativity' condition		Entropy Decomposition Rules violating 'negativity' condition	Gini Decomposition Rules violating 'negativity' condition
	$\tilde{v}_k(T_{c=1})$	$\tilde{v}_k(T_{c=1.1})$	$\tilde{v}_k(T_{c=2})$	$\tilde{v}_k(G)$
2002 (Wave 2)				
Age	-100.27	-68.20	5.37	10.18
Happiness: Direct	-11.24	-7.72	-0.02	-0.08
Happiness: Indirect	1.52	1.04	0.00	0.01
Graduates	0.89	2.08	3.45	5.33
Females	43.82	32.08	3.97	5.95
City	-8.18	-5.40	0.28	0.47
Poor Health: Direct	1.52	1.14	0.14	0.27
Poor Health: Indirect	1.25	0.94	0.11	0.22
Occupational Structure	5.13	4.66	2.59	4.01
Obligatory Work Hours	-0.39	3.21	7.84	13.86
Individual Random Effects	71.73	59.22	31.89	27.52
General Random Effects	94.22	76.95	44.38	32.27
Total	100	100	100	100
2003 (Wave 3)				
Age	-112.53	-75.82	4.96	8.36
Happiness: Direct	-10.78	-7.44	-0.01	-0.07
Happiness: Indirect	1.46	1.01	0.00	0.01
Graduates	0.78	2.11	3.69	5.28
Females	44.04	32.60	4.57	6.27
City	-7.52	-5.04	0.33	0.46
Poor Health: Direct	2.03	1.52	0.21	0.35
Poor Health: Indirect	1.67	1.25	0.17	0.29
Occupational Structure	4.13	4.27	2.89	4.01
Obligatory Work Hours	-3.85	1.62	8.38	13.56
Individual Random Effects	81.31	66.37	35.71	28.78
General Random Effects	99.25	77.54	39.10	29.42
Total	100	100	100	100
2004 (Wave 4)				
Age	-117.78	-80.15	4.59	6.53
Happiness: Direct	-10.49	-7.32	-0.02	-0.07
Happiness: Indirect	1.42	0.99	0.00	0.01
Graduates	0.67	1.95	4.04	4.99
Females	43.80	32.64	4.86	6.13
City	-7.27	-4.91	0.36	0.44
Poor Health: Direct	2.09	1.56	0.23	0.35
Poor Health: Indirect	1.72	1.28	0.19	0.29
Occupational Structure	4.11	4.26	3.19	3.86
Obligatory Work Hours	-2.77	2.17	8.99	13.10

Individual Random Effects	82.33	67.20	36.22	28.06
General Random Effects	102.16	80.32	37.34	31.16
Total	100	100	100	100
2005 (Wave 5)				
Age	-111.17	-76.53	3.70	5.35
Happiness: Direct	-9.42	-6.65	-0.01	-0.05
Happiness: Indirect	1.27	0.90	0.00	0.01
Graduates	0.90	2.09	3.80	4.96
Females	41.12	30.74	4.66	5.87
City	-6.45	-4.43	0.35	0.40
Poor Health: Direct	2.20	1.68	0.26	0.42
Poor Health: Indirect	1.81	1.38	0.21	0.34
Occupational Structure	4.45	4.34	2.90	3.74
Obligatory Work Hours	-0.60	3.06	8.12	12.56
Individual Random Effects	74.41	61.67	33.90	26.17
General Random Effects	101.47	81.74	42.09	34.19
Total	100	100	100	100

Appendix Table A1: Contributions of Explanatory Variables to Income (Percentages)

Income Quintiles	Age	Happiness	Happiness induced Work loss	Graduates	Females	City	Poor Health	Poor Health induced Work loss	Occupa-tional Structure	Obligatory Work Hours	Individual Random Effects	General Random Effects
2002 Wave 2												
1	374.77	35.94	-4.86	16.87	-125.38	26.57	-4.15	-3.41	-3.08	43.58	-109.33	-147.52
2	171.73	14.02	-1.89	6.01	-48.13	9.70	-2.60	-2.14	-1.14	17.25	-30.87	-31.93
3	102.40	7.87	-1.06	5.97	-25.62	5.97	-0.78	-0.64	1.41	24.05	-9.64	-9.93
4	70.02	5.11	-0.69	6.40	-13.48	4.23	-0.37	-0.30	2.97	22.80	2.32	1.00
5	39.38	2.82	-0.38	6.23	-4.58	2.50	-0.18	-0.15	3.34	14.76	17.20	19.06
All	81.86	6.46	-0.87	6.60	-18.70	5.05	-0.69	-0.57	2.28	19.57	0.02	-1.01
2003 Wave 3												
1	351.81	31.13	-4.21	15.60	-111.93	23.06	-5.08	-4.17	-2.30	39.12	-105.95	-127.09
2	163.29	13.40	-1.81	6.01	-46.05	9.66	-3.05	-2.51	-1.32	18.09	-26.92	-28.79
3	102.41	7.79	-1.05	6.38	-26.00	5.86	-1.00	-0.82	1.76	24.91	-10.49	-9.74
4	70.34	5.05	-0.68	6.35	-13.21	4.08	-0.51	-0.42	2.88	22.91	2.51	0.69
5	40.25	2.84	-0.38	6.47	-4.58	2.58	-0.24	-0.20	3.49	14.97	18.12	16.67
All	82.79	6.40	-0.87	6.76	-18.71	5.03	-0.90	-0.74	2.35	19.89	0.02	-2.03
2004 Wave 4												
1	345.88	28.89	-3.91	16.25	-104.53	20.94	-4.89	-4.02	-1.28	36.31	-98.97	-130.67
2	155.58	13.04	-1.76	6.57	-44.11	9.17	-2.80	-2.30	-0.98	18.16	-26.78	-23.79
3	97.68	7.57	-1.02	6.29	-24.65	5.70	-0.87	-0.71	1.89	23.86	-8.76	-6.98
4	68.39	4.96	-0.67	5.95	-12.67	4.03	-0.47	-0.39	2.97	22.47	2.26	3.16
5	39.75	2.82	-0.38	6.58	-4.65	2.50	-0.24	-0.20	3.46	14.73	17.74	17.89
All	81.26	6.29	-0.85	6.80	-18.21	4.87	-0.86	-0.70	2.44	19.46	0.01	-0.51
2005 Wave 5												
1	325.77	26.33	-3.56	14.12	-93.92	19.23	-5.36	-4.41	-1.69	31.35	-91.44	-116.43
2	144.20	12.00	-1.62	6.41	-41.92	8.54	-2.75	-2.26	-0.50	18.10	-22.31	-17.88
3	94.30	7.19	-0.97	6.22	-23.40	5.41	-0.96	-0.79	1.77	24.03	-8.07	-4.71
4	66.06	4.78	-0.65	6.70	-12.35	3.80	-0.48	-0.39	3.00	21.69	1.35	6.48
5	38.03	2.69	-0.36	6.05	-4.37	2.39	-0.24	-0.20	3.26	14.11	16.82	21.82
All	78.08	5.97	-0.81	6.65	-17.35	4.62	-0.91	-0.74	2.35	18.80	0.01	3.34

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