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RESEARCH PAPER

Effects of Happiness on Income and Income Inequality

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Abstract
This paper examines the effects of happiness on income and income inequality. We postulate 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. These direct and indirect effects of happiness on income are tested in a regression model and the implication of these effects for income distribution is explored using an inequality decomposition framework. An empirical exercise based on Australian HILDA panel survey data (2001–2014) reveals that happiness has a positive and significant effect on income generation and contributes to the reduction of inequality.

Keywords Happiness · Life satisfaction · Income · Inequality decomposition · Work hours · Health

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 (Easterlin, 1995; Frijters et al., 2004; Graham, 2010; Paul & Guilbert, 2013; Stevenson & Wolfers, 2008). However, relatively little attention has been paid to whether happier individuals perform better financially. This reverse causality could arise for various reasons. Happiness has several correlates such as self-esteem, creativity, discipline, and cognitive abilities that affect the economic and strategic decision making leading to higher income (Ifcher & Zarghamee, 2011; Isen, 2008; Kenny, 1999). A study by De Neve and Oswald (2012) shows that greater subjective well-being is associated with neurological variation, which, in turn, is associated with improved cognitive skills and economic outcomes. Based on panel data for Russia, Graham et al. (2004) reveal that happiness levels in 1995 have a positive effect on income levels in 2000. All these results provide reasons to believe that there could be a causality running from happiness to economic outcomes.

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If happiness has a significant effect on income, then it is natural to ask how this relationship is affecting the level of income inequality. This has not yet been explored. In this paper we investigate this using a regression-based income inequality decomposition approach. This approach is implemented in two stages. In the first stage, the effects of happiness and other control variables on income are examined in a regression model. In the second stage, the estimated regression is incorporated into a decomposable inequality measure to find the effects of happiness and other regression variables on income inequality.[1] An empirical illustration based on Australian HILDA panel survey data (2001–2014) is presented. The exercise reveals that happiness has a positive and significant effect on income. In percentage terms, this effect is found stronger for those at lower levels of income and weaker for those individuals at higher levels of income. These disproportionate effects of happiness resulted in a reduction in income inequality.

The rest of this paper is organised as follows. Section 2 discusses regression-based income inequality decomposition framework which forms the basis of our analysis. Section 3 presents an empirical illustration based on Australian HILDA panel survey data. Section 4 summarises and brings together the conclusions.

2 The Regression-Based Income Inequality Decomposition Approach

There can be two possible channels through which happiness might affect income generating capacity of an individual. It is postulated that happiness directly enhances the performance of an individual in earning activities. This is what we call a direct or productive effect of happiness on income generation. Happiness can also affect income indirectly via its impact on the allocation of time for paid work. This is called an indirect effect of happiness on income. 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 and thus are jointly produced and consumed. These goods are time-consuming and thus have opportunity cost. 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 persons in the market. A happy person might prefer to work more hours per week, leading to an increase in production and earnings. Or, alternatively, a happy person may like to enjoy more leisure time to consume relational goods and thus work less hours per week, resulting into an income loss. This income loss is the opportunity cost of consuming relational goods (leisure).

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.

[1] This regression-based inequality decomposition approach is not new. Paul and Dasgupta (1989) were the first to use this approach to examine the contribution of inheritance to wealth inequality in Punjab, India. Morduch and Sicular (2002) applied this approach to account for income inequality in rural China.

It is also important to note that certain other variables such as 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.[2] 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. These effects are largely empirical in nature and thus shall be tested in the regression model discussed below.

2.1 The Regression Model

Consider the following income generating function

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

where $\mathrm{Y_{it}}$ is the total income (in Aus$) of individual i during time period t. $\mathrm{H_{it}}$ is the self-reported overall life satisfaction (happiness) taking values between 0 ('totally dissatisfied') and 10 ('totally satisfied') as reported in the HILDA surveys.[3] The happiness scores are assumed to be cardinal numbers. The function $\mathrm{g(A_{it})}$ represents an 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 is assumed to be random with zero mean and constant variance,σ_s^2. The second error term 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, $\sigma_\phi^2 = \sigma_s^2 + \sigma_\varepsilon^2$.

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 & Welch, 1992). 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-Mireaus, 1982; Paul & Dasgupta, 1989).[4] 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

[2] 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 (2007).

[3] In the literature, the word 'happiness' is used, even though the data are on 'life satisfaction'. Within economics, the two are often conflated but in other disciplines and in the wider world there is a broader feeling that happiness is a short-run concept and life satisfaction is both broader and longer-run. Subjective well-being is another term used to refer to happiness in the literature (De Neve and Oswald, 2012). In this paper, we use the terms happiness and life satisfaction interchangeably to avoid any confusion.

[4] The age-income hump can be represented by regressing log income of age and age^2, happiness and other variables. In that case, one can examine the effects of these regression variables on the inequality of log income. This is not of our interest. We are interested in examining how different variables affect the inequality of income. Hence the reason for using Y rather than log Y in Eq. (1).

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

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

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

$$\begin{aligned} V_{1it} &= (A_{it} - 15)d_{1it} + 10(d_{2it} + d_{3it}) \\ V_{2it} &= (A_{it} - 25)(d_{2it} + d_{3it}) \\ V_{3it} &= (A_{it} - 35)^2 d_{3it} \end{aligned}$$

with d_{jit}, $j = 1, 2, 3$, as dummies for being aged less than 25, 25 to 34 and 35 or more.

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

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

where W is 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.[5]

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 heterogeneity (s_i). The HT estimator is based on certain assumptions. First, s_i represents time-invariant individual-specific random effect. Second, the time-invariant exogenous variables are not correlated with s_i and error term ε_{it}. Third, the time-varying exogenous variables are also not correlated with s_i and ε_{it}. Finally, the number of time-varying exogenous variables should be greater than or equal to time-invariant endogenous variables.[6]

As pointed out earlier, 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.

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

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 Eqs. (3), (4) is also estimated using the Hausman-Taylor method to account for the endogeneity of happiness. If φ_1, φ_2

[5] These variables are explained in Sect. 3.

[6] For the benefit of readers, details on Hausman and Taylor (1981) instrumental variable method (HT) are provided in "Appendix B".

and ϕ_3 are statistically significant, then the second, third and fourth terms in Eq. (4) will represent those portions of work-hours that are induced (or constrained) by happiness, poor health, and being female, respectively. The remaining part $(\varphi_0 + \eta_i + e_{it})$ represents the 'obligatory-work-hours' (OW) of a healthy but 'totally unsatisfied' man.

Substituting (4) into (3) we have

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

Note that β and $(\gamma_1\varphi_1)$ are respectively the direct and indirect effects of happiness on income, whereas γ_3 and $(\gamma_1\varphi_2)$ 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 Eq. (3), we obtain the combined residual term ϕ_{it} $(= s_i + \varepsilon_{\mathrm{it}})$ but not the separate estimates of s_i and ε_{it}. However, given ϕ_{it}, $\sigma^2_{s_i}$ and $\sigma^2_{\varepsilon_{\mathrm{it}}}$ one can obtain the minimum variance estimate of s_i as (King and Dicks-Mireaus, 1982, p 252):

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

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

For the tractability of variables in inequality decomposition analysis, Eq. (5) may be rewritten as

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

where

$$\begin{aligned} \mathrm{Z_{kit}} =&[1\ \ H_{\mathrm{it}}\ \ H_{\mathrm{it}}\ \ V_{1\mathrm{it}}\ \ V_{2\mathrm{it}}\ \ V_{3\mathrm{it}}\ \ \mathrm{OW_{it}}\ \ \mathrm{Graduate_{it}}\ \ P_{\mathrm{it}}\ \ P_{\mathrm{it}}\ \ \mathrm{Female_{it}} \\ &\mathrm{Female_{it}}\ \ \mathrm{City_{it}}\ \ \mathrm{Professional_{it}}\ \ \mathrm{White\ collar_{it}}\ \ \mathrm{Blue\,collar_{it}} \\ &\mathrm{Others_{it}}\ \ \tilde{s}_i\ \ \tilde{\varepsilon}_{it}] \end{aligned}$$

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 $(\gamma_0 + \gamma_6\,\mathrm{Professional}_{it} + \gamma_7 \mathit{White\ collar}_{it} + \gamma_8\,\mathit{Blue\ collar}_{it} + \gamma_9\,\mathit{Others}_{it})$. Since there is no interaction term in our income generating model, the income flows serve as mutually exclusive components.

2.2 Decomposition of Income Inequality by Regression Variables

To explore the implications of above discussed causal relations for income distribution we need inequality measures that are decomposable by regression variables. All the measures of income inequality, except Atkinson indices, can be written as a weighted sum of incomes (time script t is suppressed throughout this sub-section). If I denotes a measure of inequality then

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

where for a given income distribution vector $Y = (Y_1, Y_2, \ldots, Y_n)$, $w_i(Y; I)$ is the distributional weight associated with Y_i (Shorrocks, 1982). Substituting $\sum b_k Z_{ki}$ for Y_i, we have

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

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.

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

The distributional weights $w_i(Y;I)$ vary with inequality measures, so are their decomposition rules. However, not all the decomposition rules are acceptable for decomposing inequality. A decomposition rule must satisfy the 'negativity' property proposed in Paul (2004).[7] This property says that if each person receives a constant positive income from a source variable then inequality must decline. This condition is satisfied if the sum of distributional weights is negative, i.e. $\sum_i w_i(Y;I) < 0$. As shown in Paul (2004, pp. 441–442), decomposition rules of only a sub-class of the entropy measures with inequality aversion parameter $0 < c < 2$ meet the negativity requirement. The decomposition rules for Gini index and the generalized entropy indices for $c \leq 0$ and $c \geq 2$ fail to satisfy this requirement. Therefore, we consider generalized entropy measures for inequality aversion parameter $0 < c < 2$ and use their decompositions rules to examine the contribution of regression variable to income inequality. The generalized entropy indices are expressed as

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

where $w_i(Y;T_c) = [1/\{nc(c-1)\,\mu^c\}](Y_i^{c-1} - \mu^{c-1})$ is the distributional weight associated with Y_i. The parameter c reflects different perceptions of inequality with lower values indicating a higher degree of 'inequality aversion'. In other words, a lower value of c gives greater weights to income transfer at the lower side of the distribution and lower weights to income transfer at the upper side of distribution. The choice for parameter c allows researchers to see how inequality changes to their perception of inequality aversion. The decomposition rule for this measure is expressed as

7 Morduch and Sicular (2002) call this the property of *equal additions*.

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

For c = 1

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

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

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

We select two decomposition rules (Eqs. 13 and 15) of generalized entropy measure at c = 1.1 and 1.0. These rules satisfy the desirable negativity condition and allow us to see the sensitivity of inequality decomposition results to the choice of inequality aversion parameter c. The parameter c = 1 reveals greater degree of inequality aversion than c = 1.1.

3 Empirical Results

3.1 Data

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 thereby on inequality. The variables used in the estimation of Eqs. (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 expressed in Aus$. 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 entropy inequality measures which require log value 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 7 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

Table 1 Summary statistics of variables for the sample period 2001–2014 and selected years. Source: Author's calculations. We present min. and max. values along with standard deviation only for continuous variables. All binary variables take 0 and 1 values

Variables	2001–2014 (Wave 1 to Wave 14)	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
Income (Aus$ at 2014 prices) mean	46,858	40,833	43,328	49,856	50,582
Min*	1	1	1	1	1
Max	844,211.3	563,558.6	517,710	685,194	774,346
SD	39,899.7	33,423.4	34,459.1	42,462.2	42,503.5
Age (in years) mean	44.24	43.63	44.08	44.07	44.77
Min	15	15	15	15	15
Max	89	82	84	85	89
SD	13.7	12.7	13.4	14.0	14.2
Happiness (scores) mean	7.9	8.0	7.8	7.9	7.9
Min	0	0	0	0	0
Max	10	10	10	10	10
SD	1.3	1.5	1.3	1.3	1.2
Work hours per week mean	36.7	37.6	36.8	36.4	36.0
Min	0	1	0	0	0
Max	150	120	110	144	150
SD	15.6	16.7	15.9	15.1	15.2
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

Table 1 (continued)

Variables	2001–2014 (Wave 1 to Wave 14)	2001 (Wave 1)	2005 (Wave 5)	2010 (Wave 10)	2014 (Wave 14)
Entropy 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	126,258	8461	8209	8603	10,895

*0 income appears $1 as the minimum because $1 is added to each person's income so that we could take their log values required for computing inequality measure. This point is discussed in Sect. 3.3

Table 2 Distribution of individuals by life satisfaction scores (percentages). Source: Author's calculations

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

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 standard deviation of work-hours also shows a decline over the years. The average age of a person in the sample does not seem to increase over the years. This implies that there is some attrition in the data set and new respondents are interviewed each year. All large sized panel surveys are confronted by sample attrition and non-response rate. The re-interview rate of previous wave respondents provides a good indication of the trends in sample attrition, rising from 87% in HILDA survey wave 2 to over 96% by wave 9, and remaining at that level since (Watson & Wooden, 2012). While these response rates imply levels of attrition that are non-trivial, they compare favourably with the rates achieved over the first 11 waves in other panels, such as the German Socio-Economic Panel and the British Household Panel Survey (Watson & Wooden, 2014).

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 Table 2, 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.

3.2 Estimates of Income Generating Model

Tables 3 and 4 present the Hausman-Taylor estimates of the income generating function (3) and work-hours Eq. (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 ($\beta = 330.77$) which suggests that happiness directly augments the performance of an individual in earning activities. There are positive and negative character straits of happiness. Creativity, optimism, and self-discipline are the positive character traits whereas stress and pessimism are the negative (bad) traits of happiness. It is the positive character traits of happiness that enhance the productive efficiency of an individual.

Table 3 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	−10,008.39	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	−11,623.13	1060.15

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

$\sigma_s = 43{,}810.64$

$\sigma_\varepsilon = 25{,}329.62$

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

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 ($\phi_1 = -0.41$), 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 \$2148 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 [$\eta = (100/\overline{Y})\partial Y/\partial H$ =(100/50582) (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

Table 4 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

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.[8]

The coefficients of V_1 and V_2 in Eq. (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 4). 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 \$12,404.69 (= 10,008.39 + 2396.30) less than males. University degree holders earn \$7973 more than those who do not have a university degree. Those who live in big cities earn

[8] 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 = $3.0 \times 4/10 = 1.2$. 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.

Table 5 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

about \$3523 more than those who live in smaller cities. This is understandable since big cities offer 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.

3.3 Contributions of Happiness and Other Regression Variables to Income Inequality

In this section we discuss the contributions of happiness and other regression variables to income inequality. Since the contributions of these variables to inequality may not change on a year to year basis, we present inequality decomposition results only for selected years—2001, 2005, 2010 and 2014. Table 5 presents the decomposition results based on the entropy rule $\tilde{v}_k(T_{c=1.0})$. We observe that during 2001 happiness accounts for a reduction in income inequality by 12.83 per cent through its direct (efficiency) effect, but increased it by 4.5 per cent through its indirect effect (via a reduction in work hours). Thus, happiness accounts for 8.33 per cent net reduction in income inequality. Happiness is also seen to be accounting for a similar reductions in inequality in other 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 6). These disproportionate effects on income are plausible as the positive character

Table 6 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
2001 (Wave 1)								
1	577.44	41.20	−14.45	16.97	−89.34	−21.39	33.49	−1.33
2	182.75	10.41	−3.65	4.19	−24.02	−5.75	8.18	−0.36
3	131.66	6.93	−2.43	3.79	−13.29	−3.18	6.06	−0.20
4	102.00	5.12	−1.79	4.39	−8.12	−1.95	4.86	−0.14
5	65.04	3.12	−1.10	4.23	−2.93	−0.70	3.08	−0.09
All	211.78	13.36	−4.68	6.72	−27.54	−6.59	11.13	−0.42
2005 (Wave 5)								
1	427.64	32.95	−11.55	13.39	−73.17	−17.52	28.45	−1.29
2	168.96	9.61	−3.37	5.07	−22.57	−5.40	8.07	−0.44
3	125.23	6.47	−2.27	4.05	−12.63	−3.02	5.69	−0.24
4	97.96	4.80	−1.68	4.83	−8.02	−1.92	4.58	−0.16
5	62.46	2.95	−1.04	4.23	−3.04	−0.73	2.86	−0.10
All	176.45	11.36	−3.98	6.31	−23.89	−5.72	9.93	−0.44
2010 (Wave 10)								
1	382.66	29.48	−10.34	13.59	−64.64	−15.48	24.95	−1.00
2	150.61	8.42	−2.95	4.03	−19.34	−4.63	7.03	−0.39
3	111.16	5.74	−2.01	3.40	−10.99	−2.63	5.27	−0.22
4	87.81	4.34	−1.52	4.59	−7.44	−1.78	4.04	−0.13
5	53.07	2.49	−0.87	3.76	−2.72	−0.65	2.45	−0.07
All	157.06	10.09	−3.54	5.87	−21.02	−5.03	8.75	−0.36
2014 (Wave 14)								
1	363.97	26.69	−9.36	16.25	−55.65	−13.32	23.52	−0.99
2	150.29	8.33	−2.92	5.32	−19.37	−4.64	7.51	−0.34
3	110.77	5.79	−2.03	4.29	−11.70	−2.80	5.26	−0.21
4	87.48	4.29	−1.50	4.87	−7.38	−1.77	4.13	−0.14
5	53.10	2.49	−0.87	3.86	−2.58	−0.62	2.48	−0.07
All	153.12	9.52	−3.34	6.92	−19.34	−4.63	8.58	−0.35

Income quintiles	Poor health–induced work loss	Occupational structure	Obligatory work hours	Individual random effects	General random effects
2001 (Wave 1)					
1	−0.78	−227.14	156.95	−154.33	-217.29
2	−0.21	−57.60	45.84	−45.47	−14.24
3	−0.11	−38.64	35.02	−21.88	−3.74
4	−0.08	−27.72	27.74	−5.61	1.30
5	−0.05	−16.06	17.40	20.16	7.88
All	−0.25	−73.43	56.59	−41.43	−45.22
2005 (Wave 5)					

Table 6 (continued)

Income quintiles	Poor health–induced work loss	Occupational structure	Obligatory work hours	Individual random effects	General random effects
1	−0.75	−184.42	121.69	−73.55	−161.88
2	−0.25	−54.08	41.80	−35.92	−11.48
3	−0.14	−36.51	33.21	−17.13	−2.72
4	−0.09	−26.34	26.06	−2.63	2.62
5	−0.06	−15.20	16.39	22.84	8.43
All	−0.26	−63.31	47.83	−21.28	−33.01
2010 (Wave 10)					
1	−0.58	−162.65	106.63	−34.37	−168.26
2	−0.23	−47.78	36.92	−22.89	−8.81
3	−0.13	−32.29	28.78	−7.93	1.86
4	−0.08	−23.54	22.91	3.71	7.08
5	−0.04	−12.75	13.79	21.41	20.13
All	−0.21	−55.80	41.81	−8.01	−29.60
2014 (Wave 14)					
1	−0.58	−146.43	93.95	−37.34	−160.61
2	−0.20	−46.80	35.48	−19.03	−13.63
3	−0.12	−31.83	28.31	−4.36	−1.37
4	−0.08	−23.07	22.70	4.57	5.91
5	−0.04	−12.62	13.69	22.04	19.14
All	−0.20	−52.15	38.83	−6.83	−30.11

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 account for a reduction in 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 6). 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 6).

To see the sensitivity of results, the inequality contributions are also obtained based upon the entropy decomposition rule, $\tilde{v}_k(T_{c=1.1})$. These contributions presented in Appendix Table 8 are very similar to those discussed above, though a few of them are somewhat different in quantitative terms. Nonetheless, our main conclusions remain intact.

4 Concluding Remarks

This study examines the causality from happiness to income and explores the implication of this relationship for income distribution. 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 results reveal that the direct effect of happiness on income is positive but its indirect income effect via reduction in work hours is negative. The indirect effect seems to indicate that happier individuals prefer to enjoy more leisure time than those who are less happy. Since the direct effect is stronger than the indirect effect, the net effect of happiness on income generation is positive and statistically 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.[9]

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. This inequality reducing role of happiness is confirmed by our income inequality decomposition analysis. In 2001 happiness led to a reduction in income inequality by 12.8 per cent through its direct (efficiency) effect, but increased it by 4.5 per cent through its indirect effect (via a reduction in work hours). Thus, net effect of happiness on income inequality turned out to be 8.3 per cent. Happiness is also seen to be accounting for a similar reductions in inequality in other years.

The research presented in this paper can be extended and improved along the following lines. First, this paper examines the direct and indirect effects of happiness, poor health, and females on income. The indirect effects of these variables is captured through their impact on work hours. The same procedure can be adopted to examine and test the indirect effects of other variables such as education, living in the city, and occupations on happiness. Thus, our results may be seen as preliminary and suggestive.

Second, the Hausman and Taylor (1981) instrumental variable method which is used to estimate the regression model, involves several assumptions. At present, there exists no statistical technique to test the validity of these assumptions. The issue of testing of these assumptions is thus left for future research.

Third, while the theory of disproportionate effects of happiness proposed here 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.[10] Fourth, the quintile regressions can also be used to test the happiness advantage to low-income earners.

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

[9] Most of happiness literature has concentrated on estimating happiness as a function of income and some control variables, the elasticity of happiness with respect to income obtained therein could be biased since income is not treated as endogenous.

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

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.

Appendix A

See Tables 7 and 8.

Table 7 Correlation matrix of explanatory variables

	V_1	V_2	V_3	Happiness	Graduate	Female	City	Work hours	Poor health	Professional	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

Table 8 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

Appendix B: Details on Hausman and Taylor (1981) Instrumental Variable Estimation Method (HT)

The Hausman and Taylor estimation not only overcomes the problem of endogeneity but also accounts for the unobserved 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. 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. Since there is no time-invariant endogenous variable in the model, no other instruments were required. All the instruments used are quite strong as they exhibit sufficient within-panel variation (see Appendix Table 9 below).

Once the instruments are specified, the *xthtaylor* command in STATA provides the HT estimates of Eq. (3) presented in the text. 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 (steps 1 and 2). These variance components are then combined to form weights. In step 4, Eq. (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).

Table 9 Within-variation of time varying explanatory variables

Variable	Mean	SD	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

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

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Availability of data and material HILDA survey data are used which are owned by Melbourne Institute, Melbourne, Australia. I do not have authority to pass on these data to anyone.

Code availability No codes are available. I have used standard regressions methods and some calculations using Xls.

Declarations

Conflict of interest The author declare that they have no conflict of interest.

Ethical approval Not required. This paper used the HILDA survey data collected by Melbourne institute, Australia. These data are widely used by researchers.

Consent to participate Not required. This paper the HILDA survey data collected by Melbourne institute, Australia.

Consent for publication I am the sole author. No consent is needed.

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