International Journal of Social Science and Economic Research

ISSN: 2455-8834

Volume: 04, Issue: 08 "August 2019"

WHAT DETERMINES LIFE SATISFACTION INEQUALITY? EVIDENCE FROM INDIA

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ABSTRACT

This paper examines the determinants of life satisfaction inequality in India using World Value Survey data. By estimating recentered Influence Function regressions and Decomposition strategy, we find that household income does not have a significant impact on life satisfaction inequality, as observed in other developed countries. However, there is a small impact for income inequality variable on increasing life satisfaction inequality in India. Similarly people perception of their relative standing in terms of their income distribution is also not affecting life satisfaction inequality in India. Moreover, the regression result and decomposition method present that non-pecuniary factors are the major drivers of happiness inequality or life satisfaction inequality like marital status, education, health conditions, employment status etc than that of economic variables like income, relative income etc are concerned. Additionally, under decomposition result, being employed is significantly associated with the widening of life satisfaction inequality. This finding is more consistent with the current labor market issues in India like, share or informal and irregular jobs, which tend to be insecure and low paid and other than that, lack of competitive skills, involuntary unemployment etc.

Keywords: Life Satisfaction, Inequality, India, Happiness, Health

JEL Classification: D63 _ H55 _ I31 _ I38

1. INTRODUCTION

Recent years have witnessed an immense works on happiness research, whether economic growth of a country has significant impact on well-being or happiness of the people in that country. In earlier period quality of life of the people has been measured in terms of wealth, income or consumption. As time went, researchers have been realised that monetary resources are one among the key determinants of happiness. Progressively researchers recognized that economic resources are insufficient to predict the well-being of the people (Stiglitz et al., 2009).

Consequently, efforts made to identify better indicators to measure well-being of people. In the field of economics, such kind of discussion is reflected in the work of Easterlin (1974), who find no long run positive relationship between economic growth and average happiness of people, later this finding is popularly known as Easterlin Paradox.

Increasing availability of different data source and recent methodological developments pave the way for the economists to come forward and showing interest to study subjective well-being more deeply. Researchers suggest different ways of measuring subjective well-being, such as evaluation method (Frey and Stutzer, 2002; Van pragg and Carbonell, 2004), Experience method (Diener and Emmons, 1984; Kahneman et al., 2004) and Eudemonic (Ryff, 1989; Hurka, 1993; Deci and Ryan, 2000), out of which the most generally used method is evaluation method, in which people are asked to provide general assessment of their life or domain of life, such as life satisfaction, happiness level, subjective well-being, financial satisfaction etc. In happiness literature all these terms are using interchangeably.

There are a large number of studies that analyse the relationship between income and happiness and identifying various determinants of happiness. But there is very handful literature that discussing happiness inequality. This is may be due to the reason that, the way the income is possible to transfer, happiness or subjective well-being is not transferable and it cannot be redistribute across the people (Becchett et al., 2014; Niimi, 2016). This might be the reason for the lack o literature on happiness inequality at the individual level except few recent works such as Stevenson and Wolfers, 2008; Van Praag, 2011; Dutt and Foster, 2011; Becchett et al., 2014; Niimi, 2018). And the available studies have been undertaken for developed Western and European countries. However, there is extensive number of macroeconomic literature that uses cross-country data (Veenhoven, 1990 and 2005) are available.

The contribution of this paper as follows, first, it is the first attempt of studying happiness inequality by taking dispersion of life satisfaction in India as other micro economic studies are conducted in other developed countries in the World. Given that, India's ranking in the World Happiness Index is relatively low in comparison with the other developing and neighboring economies; it would be interesting to know the individual determinants of both levels and overtime changes of happiness inequality. Second, this paper is make use of a decomposition methodology suggested by Fortin et al (2011), based on the Recentered Influence Function (RIF) regressions (Firpo et al. 2000). This methodology is known as generalisation of the Oaxaca-Blinder, because it can be applied to other distributional parameters than the mean. This methodology split the aggregate change in happiness inequality into two effects, the composition effect- the overall changes in the determinants of happiness inequality distribution in the

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population and coefficient or structural effect- the changes in the return to the determinants of happiness inequality (Becchett et al., 2014).

Identifying the significant determinants of happiness inequality on levels and overtime is important in the context of policy formulation, since it helps policy makers to design policies to reduce social tensions that may affect the drivers of happiness inequality directly or indirectly (Tullock, 1971; Gurr, 1994; Brown; 1996). Moreover, it is possible to differentiate the effect of those determinants that cannot be directly redistributed by the policy makers, like employment and education, from the impact of determinants that can be directly redistributed, such as income and wealth. Additionally, this paper also analyse the relative income process more clearly than previous studies when analysing the drivers of happiness inequality, as discussed in section 2.

This paper is structured as follows. Section 2 reviews the available literature on the happiness inequality. Section 3 explains the data source, measurement of happiness inequality, the econometric model, and important variables used in this study for the empirical estimation. Estimation results and interpretation are given in Section 4. Section 5 summarise the key findings and suggest some policy implications.

2. RELATED LITERATURE

The increasing evidence on happiness literature has so far analysed on the determinants of happiness and its relationship with income. In contrast, both empirical and theoretical discussion on happiness inequality at micro level is limited, although there have been a lot of literature on happiness inequality at macro level using cross-country data. As discussed in previous literatures, individual reported happiness may influenced by both observable factors like income and individual characteristics and unobservable factors such as environmental factors as included in social-role theory (Eagly and Wood, 1991). Therefore, while discussing the drivers of happiness inequality, it is equally important to include unobservable factors also. However, the inclusion of unobservable factors into the picture is beyond the scope of this paper because of data availability, and the effects of observable factors on the levels and overtime changes of happiness inequality is the main focus of this paper.

As per the macroeconomic evidence on happiness inequality, based on a correlational analysis of the 21 years (1973-2001) of data from European Union countries, Veenhoven (2005) finds a falling trend of happiness inequality in modernised economies. Veenhoven (2005) further proved the same findings more rigorously by conducting a comparison analysis of 53 countries in the world during 1990s. In addition to this, he added that, there is a weak relationship between income inequality and standard deviation of life satisfaction.

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A similar cross-country analysis has been conducted by Ovaska and Takashima (2010) to notify the determinants of happiness inequality and suggest that, income inequality and differences in health status are positively associated with happiness inequality and poor institutional quality of a country widen the existing situation. Based on a correlational analysis of 78 countries in 1999-2001, Ott (2005) also describe the relationship between institutional factors and happiness inequality. According to his findings, all the institutional factors included in his analysis such as Government consumption, transfers and subsidies and social security etc, are positively contribute to reducing happiness inequality and increasing the level of happiness.

As far as the microeconomic analysis o happiness inequality is concerned, Stevenson and Wolfers (2008) conduct a study in USA using General Social Survey (GSS) data over the period of 1972-2006 to analyse the relationship between level and dispersion of happiness. Their study conclude that, happiness inequality reduced substantially in 1970s and 1980s, and then it is increased and reversed about one-third of the decline in initial period of time. Their decomposition analysis discloses that, the main determinants of happiness inequality in US are the changes in happiness dispersion within the gender group and race group. Further, they find, observed trend in happiness inequality is different from the observed trends in income growth and income inequality. They also suggest that, non-economic factors may strongly affect the distribution of happiness than the economic factors.

Becchetti et al., (2014) find an increasing trend of happiness inequality in Germany over 1992-2007. Using German Socio-Economic Panel data (GSOEP), their empirical result suggest that, overtime changes in education have a reducing effect on happiness inequality, however, higher unemployment rate increase happiness inequality in higher rate. Further, income growth is reducing happiness inequality, but income inequality does not have a significant effect on happiness inequality in Germany, consistent with the findings of Stevenson and Worlfer (2008) for the US. Clark et al.,(2014) conduct an empirical study over a long period of time (1971-2010) using different data set show that, nations with increasing GDP per capita experienced decreasing happiness inequality despite the growth of income inequality and constant happiness levels. Their regression result supports the view that income inequality increase happiness inequality and income growth reduce the same.

Cross checking the theoretical contribution, Van Praag (2011) made a theoretical design of how the relative position concept influences individual happiness and happiness inequality. In his model, he states that, while examine the term happiness inequality, a researcher should take into consider the relative concept, how frequently a person would compare himself with others and on the degree of social transparency in society. Becchetti and his colleagues (2014) were made the first attempt to test Van Praag's contribution by including relative concept in their empirical

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estimation by defining relative income in such a way that, whether the respondent is rich or poor compared to the reference group. Their result finds a positive impact for being relatively poor and no impact for being relatively rich on happiness inequality. Recently Niimi (2018) conduct an empirical analysis in Japan using Preference Parameter Study of Osaka University for the year 2013 to identify the determinants of happiness inequality. By estimating, Recentered Influence Functions regressions, he conclude that, household income has a significant negative impact on happiness inequality, therefore relative standing is also important for determining inequality in happiness. Moreover, his regression result insists that, the fear of losing job and life after retirement is also matters for the happiness inequality with widening the situation.

As far as India is concerned, there are few studies that have examined the long run changes in happiness of Indians by using World Value Survey (WVS) or Gallup World Poll data (Inglehart et al., 2008; Easterlin and Swangfa, 2010), or studies that make comparison between India and other countries (Diener et al, 1995; Deaton, 2008). But studies on cross sectional evidence of Indian people are very few, and none of those studies haven't discussed about happiness inequality and its determinants. Brinkerhoff et al., (1997) collected two village level samples and examine the level of happiness. More than 50% of respondents from each village reported they are satisfied with their life and a very small percentage of respondents reported completely dissatisfied with their life. Biswas and Diener, 2001; Diner, 2006, surveyed sex workers in Kolkata and says that they are satisfied with their different life domains despite their unsound economic conditions.

Recently, Majumdar and Gupta (2015) made a descriptive analysis of level of happiness and life satisfaction of Indian people using World Value Survey. They conclude that, in the long run there is a clear trend of increasing happiness and what Easterlin viewed in USA is not exists in India. According to their view, Indians are more sensitive to absolute income rather than relative income changes. They reported that people, who are employed, married, healthy, and at least acquired secondary level of education, expressing more happy with their life. People who are in lower socio economic class with poor income also report equally happy as their richer reference group. People from minority religion also report more happy as Hindus. However, so far there is no any empirical study that has conducted in India to identify the significant determinants of happiness.

Following Becchetti et al (2014) empirical framework, this paper is also taking into account the reference category in order to determine the inequality of life satisfaction in India. They define the reference group by drawing the individual characteristics of same gender, age group, educational attainment and place of residence as respondents. Using this information and different econometric model this paper tries to identify the important determinants of happiness inequality in India.

3. DATA AND METHODOLOGY

3.1 Data

The analysis part is based on the data from the second (1990) and sixth (2014) waves of World Value Survey for India. WVS is one of the most comprehensive data set in this world in terms of countries covered and years, for studying the SWB. WVS has been administered 6 times. The first wave was conducted during 1980-84 period in 21 countries and final wave conducted in between 2010 and 2014, includes 60 countries. Second wave onwards (1990-1991) WVS started to collect data from India. The sample of individuals aged more than 18 years old are drawn for this study. The empirical analysis in this paper is conducted using only data from these two waves. In the second wave, the total number of observation is 2400, and in the sixth wave, 1221 observations. After excluding all the missing values (individuals, those for whom at least one variable included in the econometric analysis is missing), the total number of observations in second and sixth wave is reduced to 579 and 330 respectively.

WVS collects basic information on respondents socio-economic and demographic characteristics like, income, employment status, educational status, marital status, age, gender etc. In addition to this, they ask questions on life satisfaction, level of happiness, financial satisfaction, and other questions related to their religious faith, social capital related questions, political behavior etc.

The main dependent variable of interest in this paper is life satisfaction and the way they collected the data on this variable is by asking individuals how satisfied they are with their life through the following question:

"All things considered, how satisfied are you with your life as a whole these days?" where "1" is defined as "dissatisfied" and "10" is defined as "satisfied;"

3.2 Measure of Happiness Inequality

The methodological issue need to be bothering here is the measurement of happiness inequality. An implicit assumption of any standard inequality measure is that the variable in question is cardinal and continuous in nature, and also assumes equal distance between the ratings of the variable so that interpersonal comparison is possible. However, the popular surveys which are collecting information on people self reported happiness is categorical and ordinal in nature and WVS is also not an exception from it. It is unknown that whether the different ratings of happiness measure keeps equal distance each other.

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The assumption of cardinality is not applicable in the case of happiness, for it is ordinal in nature. However, the cardinality assumption is often used in empirical analysis. For instance, Carbonell and Frijters (2004) tested both cardinality and ordinal assumption of happiness score and find there is a small difference in the estimated result of drivers of happiness. Fray and Stutzer (2001) empirical finding is also support this view. Differ to this, Clark et al., (2014) use standard deviation as the measure of happiness inequality by assuming happiness is a cardinal variable, they also use an index of ordinal variation, a measure for ordinal variables for robustness check and obtain almost similar results. These findings are seems to be parallel with the view made by Van Praag (1991) who find that individuals tend to translate their verbal evaluations regarding their overall quality of life to a numerical scale when they answer to the subjective questions (Niimi, 2018).

Against the assumption of homogenous scale, previous studies find the presence of heterogeneity in the scales at which the respondents used to evaluate their level of happiness, however it is argued that such heterogeneity should not affect the regression result because it is expected to be random (Frey and Stutzer, 2002; Di Tella and MacCulloch, 2006). Few other empirical studies conduct various tests on heterogeneity in individual scale and find respondents use different scale when answering their welfare questions and it should not affect the estimated result, for it is not an important source of bias in the estimation (Beegle et al., 2012).

Based on the previous findings, this paper assumes life satisfaction data is a cardinal variable and uses standard deviation (variance) as the measure of happiness inequality. Kalmijn and Veenhoven (2005) investigate the applicability of various inequality matrices to quantify happiness dispersion. They used nine inequality measures by assuming cardinality scale across the happiness categories. They find four measures of happiness inequality, standard deviation, mean absolute difference, mean pair distance, and interquartile range are the efficient measures to quantify happiness dispersion. Even there is no any single superior matric to the others among these four measures, Kalmijn and Veenhoven (2005) support the use of standard deviation as the happiness inequality measure, which has been popularly used in the literature so far to quantify the inequality of happiness.

Figure 1 reports life satisfaction inequality by measuring standard deviation between the periods 1990 and 2014. Despite the initial fluctuations, there is an overall upward trend with an increase of about 0.84% or almost 1% increase over this period. This is compared with the changes in real per capita GDP. GDP per capita increased steadily with an overall increase of 6.58% between 1990 and 2014. Economic growth thus seems to have contributed to increasing life satisfaction inequality (happiness inequality) in India over the past two decades. This is against

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of the previous findings for other countries that income growth is related with the declining happiness inequality.

3.3 Econometric Model

To find out the determinants o happiness inequality, the empirical analysis is conducted by using Recentered Influence Function (RIF) regression introduced by Firpo et al (2007, 2009). There is no any strong difference between RIF regression and standard regression except the nature of dependent variable. In RIF regression, the level of life satisfaction, LS, is substituted by the Recentered Influence Function, RIF (ls; v), of the distributional parameter such as variance, Gini coefficients. It is therefore more applicable to identify the drivers of happiness inequality (variance). Sum of the distributional statistic v and the influence function IF(ls; v) provide RIF: RIF (ls; v) = v + IF (ls; v). The influence function, IF(ls; v) is a generally used technique to measure the robustness of a distributional statistic to the presence of outliers, which differentiate the impact of an individual observation on that distributional statistic. RIF is considered as a linear approximation of a nonlinear function of distributional statistic such as variance, or Gini coefficient and it helps to capture the impact of change in distribution of the covariates to the change in the distributional statistic of interest.

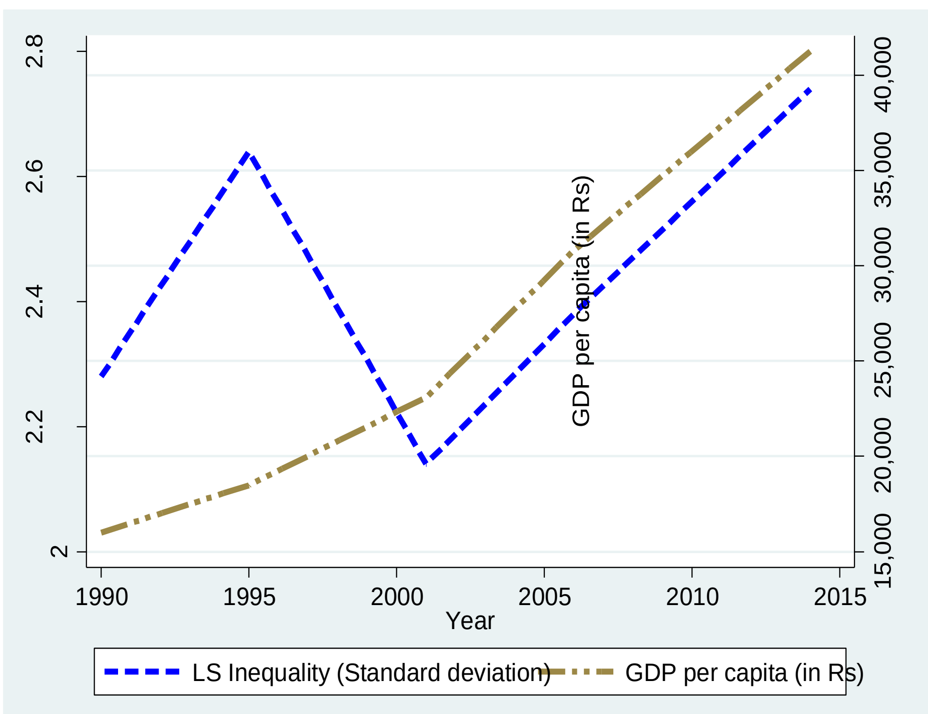

Fig. 1: Life Satisfaction Inequality and real GDP per capita (in 2004-05 prices)

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Source: Life Satisfaction Inequality: Calculations based on the WVS 1990 to 2014, 5 waves data.

GDP per capita: Calculations based on the real GDP per capita the National Accounts of India.

One basic feature of the RIF is that its expected value is equal to the distributional statistic v. According to the law of iterated expectations, the distributional statistic v can be explained in terms of the conditional expectation of the RIF on the covariates X:

$$v = E[RIF(\,LS; v)] = E_X\big[E[\,RIF(LS; v) \mid X\,]\big]$$

The conditional expectation of RIF(LS; v) can in turn, be expressed as a linear function of the covariates, obtaining the RIF regression:

$$E[RIF(LS; v) \mid X] = X\gamma^{v}$$

where the coefficient γ is the marginal effect of covariates X on the distributional statistic v and can be estimated with the help of Ordinary Least Squares (OLS). In this paper RIF regression will be estimated for the variance of life satisfaction, and will also estimating them for the Gini coefficient as a robustness check.

3.3.1 Decomposition Methodology

Let LS_{i1} be the life satisfaction of an individual i observed in period 1, and LS_{i0} the corresponding value in period 0. For each individual i the observed life satisfaction level is given by $LS_i = LS_{i1}.T_i + LS_{i0}.(1 - T_i)$, where $T_i = 1$ if individual i is observed in period 1, and 0 otherwise. Finally, let X be the vector of K explanatory variables which are observed in both periods.

The Oaxaca-Blinder (OB) helps to differentiate the overall difference in means overtime, $\Delta_0^{\mu} = \mu_1 - \mu_0$, into two components, one related to changes in the returns of the explanatory variables, the structure effect or coefficient effect, Δ_S^{μ}, and the other linked to the changes in the distribution of these explanatory variables, the composition effect, Δ_X^{μ}. This type of composition is known as "aggregate" decomposition. OB decomposition also allows to identify each explanatory variable's contribution to these two aggregate effects, that is known as "detailed" decomposition.

As discussed in earlier section, Fortin et al., (2011) extended OB decomposition, the aggregate and detailed decomposition of the mean to other distributional statistic, v, such as, median, variance, Gini coefficient or quantiles. Thus, this method is known as FFL decomposition.

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The RIF regression:

$$E[RIF(LS;v) \mid X] = X\gamma^{v}$$

where the parameter $X\gamma^{v}$, can be estimated with the help of OLS. Then, it can decompose the overall difference overtime of v, $\Delta_0^v = v_1 - v_0$, into a coefficient effect (Δ_S^v), and composition effect (Δ_X^v), $\Delta_0^v = \Delta_S^v + \Delta_X^V$, effects that can be expressed as:

$$\Delta_S^V = E[X \mid T = 1](\gamma_1^V - \gamma_0^V)$$

$$\Delta_X^V = (E[X \mid T = 1] - E[X \mid T = 0])'\gamma_0^V.$$

The main feature of the methodology suggested in this paper is that it allows to estimate the coefficient and composition effect of each explanatory variable into the changes in life satisfaction inequality.

3.4 Descriptive Findings

On average, the average level of life satisfaction in India decreased over time from 6.69 to 5.16 (-22.87%), while life satisfaction inequality increased over the period, since the variance increased by 44.53%, from 5.21 to 7.53, and the Gini index increased by 57.89%, from 0.192 to 0.304. these trends are contrary to the existing studies which conducted in developed countries. Becchetti et al (2014) find a slight decrease (2.5%) in average happiness and around 8% increase in variance of happiness and 7% increase in Gini index of happiness in Germany during 1992 to 2007. Similarly Niimi (2018) sees a downward trend in happiness inequality (standard deviation) by 7.2% in Japan during 2003 to 2013. In such a framework, this paper is the first attempt in developing countries and the Indian case is a peculiar and interesting case study to discuss happiness inequality.

To identify the factors of life satisfaction inequality in India, this paper focus on the standard socio-economic and demographic covariates that are generally used in happiness studies (age, gender, income, income inequality, relative income, education, marital status, employment status, health status, religion, general trust and geographical region). Household income question in WVS waves has been asked inconsistently by giving respondents a show card or scale with 10 income brackets, each class represented either a number or with a letter. Individuals are then asked to answer the question (followed question from WVS 1990 wave):

"Here is a scale of incomes. We would like to know in what group your household

is, counting all wages, pensions and other incomes that come in. Just give the letter of the group your household falls into, before taxes and other deductions."

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A. up to 12,000 rupees per year
B. 12001-18,000
C. 18001-24,000
D. 24001-30,000
E. 30001-36,000
F. 36001-48,000
G. 48001-60,000
H. 60001-90,000
I. 90001-120,000
J. over 120,000 rupees per year

The income variable is converted to a numerical figure by calculating the midpoint of the income categories chosen by the survey respondents (Second and fourth waves only). The highest income bracket is converted by adding the half of the difference between top and lower bounds of previous income categories to the lower bound of the highest income category (Rousseau, 2009). As for income inequality, this paper make use of two dummy variables, the first one is concerning the individuals whose income level is below 60% of median income and second on is concerning the individuals whose income is above 200% of median income.

To know the impact of reference group income (Van Praag, 2011; Becchetti et al., 2014; Niimi, 2018), this paper also construct relative income. It is obtained by calculating median income of reference group (individuals with the same place of region, same age group and same educational status) and then deriving the share of individuals whose income below (above) 60% (200%) of the median income of the reference group (Becchetti et al., 2014).

Table 1, in Appendix, implies the definition of the explanatory variables used in the analysis and Table 1 compare the mean values of the covariates in the two time periods, 1990 and 2014. The main trend viewed in WVS for this period as follows. Population is getting older and less educated. The shares of married people compared to unmarried, widowed, separated or divorced are increasing. Average income level is increased but income inequality is reducing, the share of poor people is reduced by 9.7% and that of rich people increased by 14%. On average, the share of individuals under (above) 60% (200%) of the median income of reference group reduces (increases). The employment rate is reduced slightly in the second period and also, unemployment rate is increased slightly during 6th wave of WVS, and the share of out of labour force category (inactive) is decreased. Health status of the respondents improved in the second period compared to first period. The share of respondents who do not trust others is also increased slightly in 2014.

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Table 1: Changes in the mean of explanatory variables over time

Variables	1990	2014
Female	0.46	0.38
Low Educated	0.10	0.69
Medium Educated	0.49	0.17
High Educated	0.40	0.14
Age 18-24	0.23	0.14
Age 25-34	0.28	0.26
Age 35-44	0.25	0.24
Age 45-64	0.21	0.29
Age 65 above	0.02	0.06
Married	0.69	0.82
Single	0.31	0.18
Income level	28631.52	35920.87
Poor	0.31	0.28
Rich	0.07	0.15
Relatively Poor	0.63	0.61
Relatively Rich	0.37	0.39
Living in South India	0.27	0.25
Living in East India	0.24	0.13
Living in North India	0.25	0.24
Living in West India	0.24	0.38
Employed	0.52	0.49
Unemployed	0.08	0.10
Inactive	0.40	0.34
Health- Very Good	0.19	0.31
Health-Good	0.43	0.39
Health-Fair	0.29	0.20
Health- Poor	0.09	0.08
Trusted	0.33	0.33
Not Trusted	0.61	0.64

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4. EMPIRICAL RESULTS

The empirical analysis is divided into two parts. In the section, cross sectional result on drivers of life satisfaction inequality has been presented for the time periods considered by means of the RIF regressions. The empirical result is based on two inequality indices, the variance, which is the standard inequality measure and Gini index, which is for robustness check. In the second part, the decomposition strategy has been applied to quantify the importance of coefficient and composition effects in affecting the observed changes in life satisfaction inequality.

4.1 Cross-Sectional Result

Table 2 reports the RIF regression results for the two period separately (1990 and 2014), for the variance and for the Gini index. The coefficients of the RIF regression estimate the impact of each explanatory variable on the life satisfaction inequality measure.

Given the impact of each covariate on the life satisfaction inequality, variance, plus two level of education or pre-degree has a significant and negative impact irrespective of the time period observed (Table 2), which is consistent with the findings of Becchetti et al. (2014), Clark et al. (2014) and Niimi (2018). The histogram of the life satisfaction distribution for secondary, higher secondary and higher level of education (Figure 2) shows that higher education is associated with lowering the life satisfaction inequality. It is also consistent with the happiness inequality among the educational groups has been observed in the US (Stevenson and Wolfer, 2008) and in Germany (Becchetti et al., 2014).

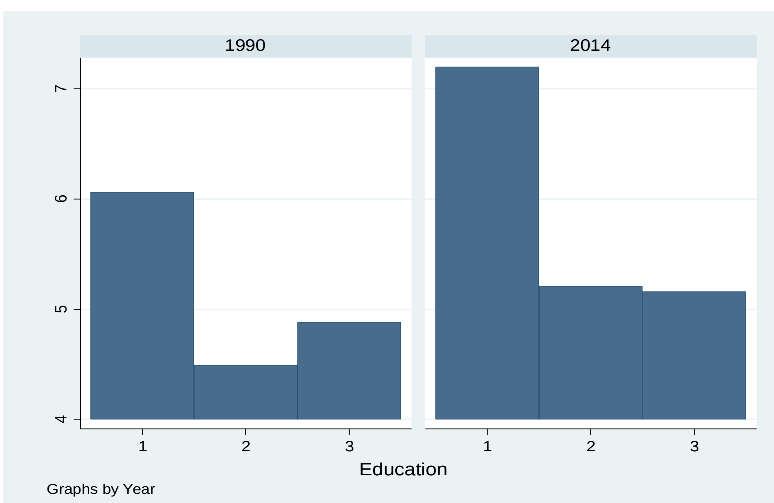

Fig. 2: Distribution of life satisfaction variance by education levels. 1: Low education, 2: Medium or plus two level of education, 3: UG or higher level of education.

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As for income level, there is no evidence of significant relation between income and life satisfaction inequality. Consequently, considering income inequality, being a poor and being a rich do not have a significant impact on life satisfaction inequality. Similar findings are obtained when considering relative income variables, i.e, being relatively poor and relatively rich. Relatively poor has a positive impact but it is non-significant.

Table 2: RIF Regressions for the two periods, for variance and Gini index

Variables	Variance		Gini	
	1990	2014	1990	2014
Female	-0.719 (0.66)	-1.01(0.918)	-0.012 (0.015)	-0.040(0.026)
+2/Pre-Degree	-1.71* (1.03)	-2.12*(1.22)	-0.050** (0.024)	-0.039(0.035)
UG/Higher Edu	-1.95 (1.21)	-0.85(1.147)	-0.058** (0.028)	-0.023(0.032)
Age 18-24	0.269 (2.07)	-0.689(2.26)	0.050 (0.048)	-0.038(0.064)
Age 25-34	2.02 (2.07)	0.195(2.109)	0.086* (0.048)	-0.050(0.060)
Age 35-44	2.40 (2.10)	0.445(2.091)	0.082* (0.048)	-0.020 (0.060)
Age 45-65	2.38 (2.04)	1.23(2.06)	0.072 (0.047)	-0.042 (0.059)
Married	-1.80**(0.71)	1.39(1.04)	-0.045***(0.016)	0.031 (0.030)
Log Income	-0.26 (0.896)	-0.859(1.08)	-0.009 (0.020)	-0.012(0.030)
Poor	-0.436 (1.58)	-2.65(2.14)	0.011 (0.037)	-0.023 (0.061)
Rich	1.33 (1.29)	1.22(3.63)	0.026 (0.030)	-0.257**(0.104)
Relatively Poor	1.52 (2.03)	2.55(4.09)	0.032 (0.047)	-0.166 (0.117)
South India	-0.695 (0.89)	1.40(1.57)	-0.001 (0.020)	0.081 (0.045)
North India	1.18 (0.893)	7.79(1.51)	0.032 (0.020)	0.145 (0.043)
West India	0.662 (0.799)	3.39(1.47)	0.035*(0.018)	0.193 (0.042)
Employed	1.09 (1.14)	-3.26***(1.14)	0.005 (0.026)	0.020 (0.032)
Inactive	1.96* (1.17)	-2.08(1.36)	0.033(0.027)	0.009 (0.039)
Not trusted	-0.031 (0.608)	-1.24(0.781)	-0.004(0.014)	-0.014 (0.022)
Very Good Health	-2.38* (1.27)	2.21(1.38)	-0.139***(0.029)	0.059 (0.039)
Good Health	-3.70*** (1.13)	0.136(1.33)	-0.131***(0.026)	0.017(0.038)
Fair Health	-1.48 (1.12)	1.90(1.52)	-0.063** (0.026)	0.019 (0.043)
Muslim	-0.756 (1.13)	1.61 (1.18)	0.001 (0.026)	0.071** (0.034)
Christian	-1.49 (1.65)	3.01** (1.39)	-0.053 (0.038)	0.042 (0.040)
Others	-3.36* (2.00)	-0.870 (1.42)	-0.041 (0.046)	0.0003 (0.040)

Constant	9.72	13.46	0.345	0.496
Observations	579	330	579	330
R^2	0.08	0.2425	0.1341	0.1734

***, **, * Statistical significance at 1, 5and 10% level. Standard errors are in parenthesis

As for the marital status, being married reduces life satisfaction inequality earlier period and it is significant at 5% level. But later the impact of being married on life satisfaction inequality is positive but non-significant. Figure 3 shows that trends of variance indexes computed by marital status in the two time periods resemble those of corresponding RIF regression coefficients.

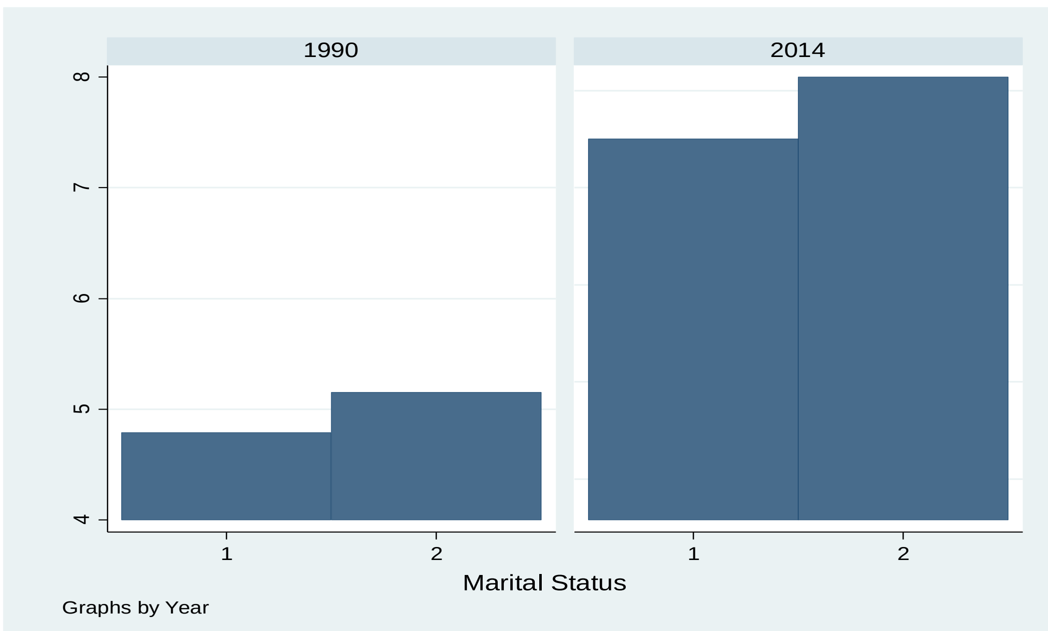

Fig. 3: Distribution of life satisfaction variance by marital status. 1: Married, 2: Single

With regard to the effect of health on life satisfaction inequality, this is observed a negative and significant impact of respondents who report very good and good health status on life satisfaction inequality during 1990, but it becomes positive and insignificant in 2014. This can be observed in Figure 4, where variance indexes by health status are reported. The impact of employment status is concerned, being employed reduces life satisfaction inequality in 2014 and the impact is significant at 1% level. While being inactive has a significant positive impact on life satisfaction inequality in earlier period. But later it produces a negative and insignificant impact. Finally, being a Christian increases life satisfaction inequality, it is point out the insecurity faced by minorities in India due to the extreme religious and caste issues.

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As a robustness check, Table 2 also reports RIF regression using the Gini Index. It is important to note that there is no significant difference with respect to the coefficients computed in the variance analysis, i.e. same signs and statistical significance, however, the results obtained through Gini index in 1990 is more strong and efficient by adding few more significant variables.

Compared to the 1990 variance result, the coefficient value obtained through Gini index provide significant and negative impact for both higher secondary and UG or higher level of education on life satisfaction inequality. With regard to the effect of age on life satisfaction inequality, it is observed a positive and significant impact for the age group 25-34 and 35-44. Living in West India increases inequality of life satisfaction compared to other areas. But the impact is increasing and becomes insignificant later. Under health status, compared to 1990 variance result, Gini index produce additional significant impact for fair health also.

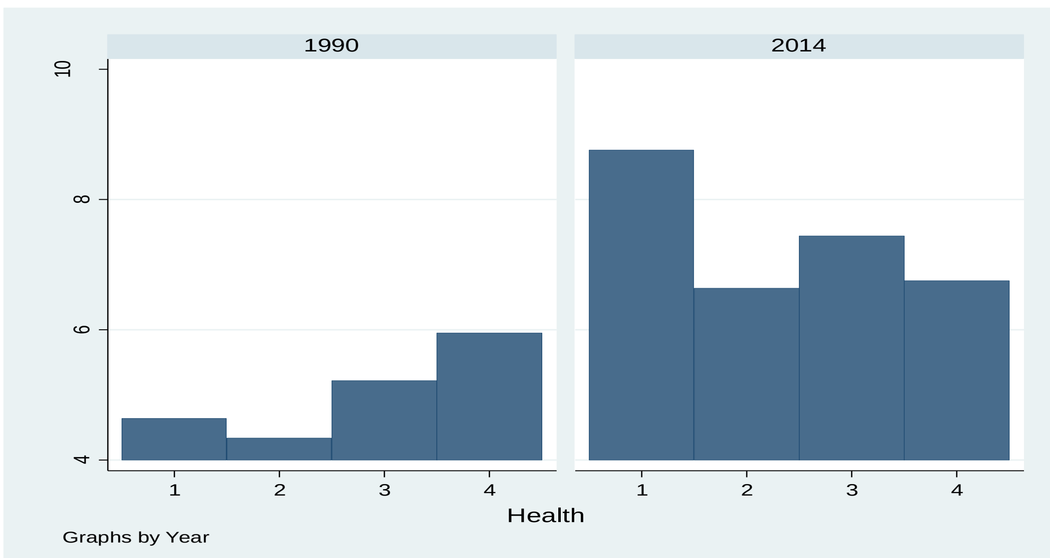

Fig. 4: Distribution of life satisfaction variance by health status.
1:Very good, 2: Good, 3; Fair and 4: Poor

2014 Gini index result produce a negative effect for being a rich category on life satisfaction inequality. This is slightly support the view that as income increases happiness inequality tend to decrease. But still the income impact on life satisfaction inequality is not clear in India. As religion is concerned, being a Muslim increases life satisfaction inequality according to the 2014 Gini index result. The explanatory of the regression increases for two statistics as time varies. But the highest R^2 value (0.2425) is reported by the regression result that obtained from variance for the second period; similarly the smallest value is also reported by variance based regression

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result for the period 1990. The explanatory power of regression that obtain when Gini index as thee distribution statistic is more or less stable, 0.1341 for 1990 and 0.1734 for 2014.

Cross-sectional result on RIF regression estimate conclude that, in India, the life satisfaction inequality is mostly determined not by pecuniary factors, like income or income inequality, it is by non-pecuniary factors like education, health and marital status.

4.2 Decomposition Result

The results of decomposition analysis of the variance are shown in Table 3, which includes also the decomposition results for the Gini index as a robustness check. As a general information, the coefficient effect is partially explains the variation in variance overtime. This suggests that the impacts of the determinants of life satisfaction inequality remain not stable overtime. While composition effect is almost insignificant, i.e. the contribution of almost all variables to the composition effect is insignificant. Hence, the interpretation of decomposition result is more focus on the analysis of the coefficient effect.

From the impact of specific covariates, five main findings emerge. First, marital status negatively affects the variation of life satisfaction inequality, as people getting married overtime; the variance of life satisfaction inequality would have decreased by 2.61 units. Marriage is beneficial due to several reasons like, as psychologists say, emotional support, love, companionship and security, as sociologists think of monogamy and as economists believe, division of labour, specialization and financial benefits as a couple may ensure physical as well as mental well-being.

Second, interesting result emerges from the place of residence. Living in North Indian states compared to Eastern states (Bihar, West Bengal and Odisha) of India have a strong and significant tend to reduce (-1.66) the evolution of life satisfaction inequality. Compared to Eastern states, North Indian States (UP, Punjab, Haryana Jammu and Kashmir) having the privilege of better governance, increasing per capita income, low level of poverty etc may affect the distribution of life satisfaction.

Third, the increase in the employment rate overtime has a negative impact on life satisfaction inequality due to the fact that employment coefficient is positive (2.36) and it is significant at 5% level. Same way, the impact of inactive people (out of labour force) is also increase the life satisfaction inequality (1.27). This result pays the particular attention over the existence of labor market insecurity in India, like growing youth unemployment rate, increasing trend of informal or irregular employment, fear of losing job in future due to the lack of skills and competitive capabilities, etc may affect the distribution of life satisfaction. Moreover, people may choose to

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be unemployed as they feel that wage payment is not enough to compensate their work effort and prefer to be unemployed and receive unemployment benefit (Majumdar and Gupta, 2015).

Fourth, favorable health status has a strong favorable impact on reducing life satisfaction inequality overtime. In particular, the increase in share of people who report very good health condition generate a significant positive impact, that, however, accounts for -1.46 unit of the total variance variation, individual who report good health, accounts, -1.61 variance variation and people who report fair health accounts, 0.543 variance variation in life satisfaction inequality overtime. As the shares of health status changes overtime, the variance of life satisfaction inequality would have decreased by 3.613. This evidence suggest that the poor health status of the people observed in India can be considered as one of the strong driving forces of increasing happiness inequality, because of the large size of the impact.

Fifth, under religion; being a Christian, reducing the variance variation of life satisfaction inequality overtime. More specifically, the overtime change in the share of Christian people explains -0.437 units of the variance variation, while other religions have no effects. Furthermore, increase in the income level, and income inequality has no significant impact on life satisfaction inequality, similarly reference group income also. This also suggest that the non-pecuniary factors of life satisfaction, such as education, marital status, employment status, health status, place of residence and religion have taken into account to explain the changes in life satisfaction inequality. This result is also consistent with the findings of Stevenson and Wolfers (2008) and Becchetti et al. (2014) where the income and happiness inequality relation has been studied and observed that, non-pecuniary factors are important in shaping the evolution of happiness inequality.

Table 3 also presents the decomposition results when using the Gini index as distributional statistic. Interestingly, main results are more similar to the ones obtained after using the variance as distributional measure except slight differences. The result which is obtained through Gini index is considered as robustness check to the analysis. However, using the Gini index confirming one fact that, changes in the index overtime are due to the changes in both covariate composition and coefficients. Moreover, here observed results which are substantially equal to what observed previously, including the favourable impact of education, overall slight positive impact of age and income inequality (being a rich person). Finally, also the shares of each explanatory variable as contribution of the total variation of the Gini index are very close to the results that are obtained for the variance.

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Table 3: Decomposition of Life Satisfaction inequality changes: composition and coefficient effects, for variance and Gini index.

Variables	Variance		Gini	
	Composition	Coefficient	Composition	Coefficient
Female	-0.052 (0.053)	0.098 (0.380)	-0.001 (0.001)	0.009(0.010)
+2/Pre-Degree	-0.548 (0.333)	0.057 (0.228)	-0.016**(0.007)	-0.002(0.006)
UG/Higher Edu	-0.443 (0.279)	-0.167 (0.253)	-0.013**(0.006)	-0.005(0.040)
Age 18-24	0.031 (0.244)	0.130 (0.419)	0.005 (0.005)	0.012(0.011)
Age 25-34	0.058 (0.086)	0.510 (0.825)	0.002(0.003)	0.038*(0.021)
Age 35-44	-0.137 (0.138)	0.481(0.729)	-0.004(0.003)	0.025(0.019)
Age 45-65	-0.179 (0.170)	0.347(0.880)	-0.005(.004)	0.034(0.023)
Married	0.326**(0.139)	-2.61**(1.03)	0.008**(0.003)	-0.063**(0.028)
Log Income	0.094(0.319)	5.96(14.08)	0.003(0.007)	0.031(0.375)
Poor	-0.036 (0.135)	1.25(1.51)	0.001(0.003)	0.019(0.040)
Rich	-0.206 (0.205)	0.039(1.39)	-0.004(0.004)	0.102**(0.039)
Relatively Poor	0.104(0.148)	-0.648(2.86)	0.002(0.003)	0.124(0.079)
South India	0.009(0.023)	-0.489(0.426)	0.000(0.0002)	-0.019(0.011)
North India	-0.058(0.055)	-1.66***(0.470)	-0.002 (0.001)	-0.028**(0.012)
West India	-0.106(0.130)	-1.15(0.708)	-0.005*(0.003)	-0.066***(0.02)
Employed	-0.013 (0.040)	2.36***(.885)	-0.000(0.000)	-0.007(0.022)
Inactive	0.144(0.107)	1.27**(0.576)	0.002(0.002)	0.007(0.015)
Not trusted	-0.002(0.042)	0.662(0.541)	-0.000(0.001)	0.005(0.014)
Very Good Health	0.379*(0.215)	-1.46**(0.610)	0.022***(0.01)	-0.063***(0.02)
Good Health	-0.026(0.126)	-1.61**(0.744)	-0.001(0.004)	-0.063***(0.02)
Fair Health	-0.248 (0.193)	-0.543*(0.312)	-0.010**(0.004)	-0.013(0.008)
Muslim	0.036 (0.057)	-0.287(0.203)	-0.000(0.001)	-0.008(0.005)
Christian	0.093 (0.107)	-0.437**(0.222)	0.003(.003)	-0.009*(0.005)
Others	0.199 (0.131)	-0.203(0.204)	0.002(0.003)	-0.003(0.005)
Constant		-3.73(15.75)		-0.151(0.421)
Observation	909		909	

***, **, * Statistical significance at 1, 5and 10% level. Standard errors are in parenthesis

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5. CONCLUSIONS

The contribution of this paper to the happiness literature is to identify the drivers of life satisfaction inequality both levels and overtime changes in India, and in the decomposition of life satisfaction inequality changes in composition and coefficient effects. By applying the decomposition model proposed by Fortin et al. (2011) to the WVS data in the period 1990-2014, this study find follows.

Most of the dynamics of life satisfaction inequality is explained by coefficient effect, documenting the variance across time of returns of determinants of life satisfaction, while changes in composition effects are also not negligible when Gini index is concerned.

Life satisfaction inequality has risen mainly due to the deterioration in the non-pecuniary factors such as marital status, education, and health status, place of region, religion, and labour market conditions. Further, the increase in income level cannot be considered as one of the determinant of life satisfaction inequality, while there is an unjustified proof of positive impact of increasing income inequality on increasing life satisfaction inequality.

This overall evidence suggests some policy implications like, strategies intending to improve education, health and family planning, i.e. improve the quality of education, maintain and valuing strong family relationships, improve health conditions, make sure that public health facilities should reach to the poor ones at affordable price, provide a secure and safety labour market conditions in order to avoid the insecurity or fear of losing job involved in current labour market. Additionally, higher income and lower unemployment rate and protect the needs and aspirations of the minorities in this country to maintain religious harmony and ultimately generate a spillover effect in reducing life satisfaction inequality, and in turn, enhance strong social cohesion.

APPENDIX

Table 1: Description of variables

Variable Name	Description
Female	Dummy variable that equals one if respondents are female
Low Educated	Dummy variable that equals one if respondent have completed at least 10th class
Medium Educated	Dummy variable that equals one if respondent have completed UG level of education
High Educated	Dummy variable that equals one if respondent have PG or higher level of education
Age 18-24	Dummy variable that equals one if respondent’s age is in between 18-24

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Age 25-34	Dummy variable that equals one if respondent's age is in between 25-34
Age 35-44	Dummy variable that equals one if respondent's age is in between 35-44
Age 45-64	Dummy variable that equals one if respondent's age is in between 45-64
Age 65 above	Dummy variable that equals one if respondent's age is above 65
Log Income	A continuous variable calculated by taking median of the following income class. up to 12,000 rupees per year: 6000 rupees 12001-18,000: 15,000.5 18001-24,000: 21000.5 24001-30,000: 27,000.5 30001-36,000: 33000.5 36001-48,000: 42000.5 48001-60,000: 54000.5 60001-90,000: 75000.5 90001-120,000: 105000.5 over 120,000 rupees per year: 150000
Married	Dummy variable that equals one if respondents either married or living together
Single	Dummy variable that equals one if respondents are single, divorced, separated or widowed.
Poor	Dummy variable that equals one if respondent's income is lower than 60% of the median
Rich	Dummy variable that equals one if respondent's income is greater than 200% of the median
Relatively Poor	Dummy variable that equals one if respondent's income is lower than 60% of the reference group median income
Relatively Rich	Dummy variable that equals one if respondent's income is greater than 200% of the reference group median income
Living in South India	Dummy variable that equals one if respondent is living in South Indian States (Kerala, Tamil Nadu, Andhra Pradesh, Karnataka)
Living in East India	Dummy variable that equals one if respondent is living in East Indian States
Living in North India	Dummy variable that equals one if respondent is living in North Indian States
Living in West India	Dummy variable that equals one if respondent is living in West Indian States
Employed	Dummy variable that equals one if respondents having full time job, part time job or self employment

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Unemployed	Dummy variable that equals one if respondents are unemployed
Inactive	Dummy variable that equals one if respondents are students, house wives or retired.
Health- Very Good	Dummy variable that equals one if respondents' health status is very good
Health-Good	Dummy variable that equals one if respondents' health status is good
Health-Fair	Dummy variable that equals one if respondents' health status is fair
Health- Poor	Dummy variable that equals one if respondents' health status is poor
Trusted	Dummy variable that equals one if respondents are trusting others
Not Trusted	Dummy variable that equals one if respondents are not trusting others
Religion Hindu	Dummy variable that equals one if respondents are belong to Hindu religion
Muslim	Dummy variable that equals one if respondents are belong to Muslim religion
Christian	Dummy variable that equals one if respondents are belong to Christian religion
Others	Dummy variable that equals one if respondents are belongs to Buddhism, Jainism or Sikhism.

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