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IS THE EFFECT OF INCOME ON HAPPINESS SAME FOR ALL IN INDIA? A PANEL QUANTILE REGRESSION ANALYSIS OF HETEROGENEITY IN THE RELATIONSHIP BETWEEN INCOME AND LIFE SATISFACTION

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Abstract *The OLS and ordered probit estimation of a causal relationship between income and happiness assume linearity in individual and average income effects and the same average effect holds over the entire range of subjective well-being distribution. The response of well-being to income changes is not the same for poor and rich, dissatisfied or unhappy, and satisfied or happy people. This paper estimates heterogeneity in the income-life satisfaction relationship at specific locations of subjective well-being distribution by panel quantile regression method. The data is derived from six waves of the World Value Survey for 12 major states of India for 24 years over the period 1990-2014. The descriptive analysis of well-being distribution across states shows heterogeneity in the income-well-being relationship between states and individuals within states. The across-states over-time panel quantile regression results reveal that estimation of average effect only provides an incomplete picture of the effect of income at both ends of the conditional distribution of well-being indicators, life satisfaction and happiness levels. The quantile regression estimates vastly differ not only from the mean estimates, but also across quantiles. Life satisfaction falls and happiness rises with an increase in average state income and the income effect is strong at the lower end than at the upper end of subjective well-being distribution.*

Keywords: *Life Satisfaction, Happiness, Subjective Well-Being Distribution, NSDP Per Capita, Differential Effects, Quantile Regression*

JEL Classification: *D31, I31, C23, C35, J 28, J71*

INTRODUCTION

In the happiness literature, studies that examine the nature of income-happiness relationship often observe that the "average Joe's happiness" is reducing as income increases over time. Such studies frequently use ordinary least squares (OLS) or ordered probit regressions to estimate the effect of either individual or aggregate income or income growth on the individual or average subjective well-being (SWB) indicators such as life satisfaction or happiness. The conventional regression methods estimate only the mean effects of income on well-being and do not reveal heterogeneity or differential income effects at different points in the well-being distribution. Being average estimates, such estimation methods assume a linear relationship between the dependent variable and the covariates, i.e. the same average effect holds throughout the well-being distribution. Though an understanding of such average effect of economic or income growth on a country's well-being level can provide useful insights, the averaged coefficient estimate does not reveal the complete distributional picture of the relationship between income and well-being over the entire distribution. There is no *a priori* reason that covariate effect to be the same across the entire well-being distribution, as the effects of socioeconomic factors that determine life satisfaction may vary in the lower and upper range of the well-being distribution. Or, the determinants of happiness are not the same as the determinants of unhappiness. Therefore, average effects may well be misleading and the estimation should look beyond the mean effects and capture the differential income effects at every specific location of the well-being distribution.

Such a more comprehensive picture of the differential effect of income on well-being can be estimated by the quantile regression method. The quantile regression model, similar to OLS model in terms of statistical structure, provides a

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richer characterisation of the data allowing the differential impact of income on the entire distribution of well-being, not merely its conditional mean, as in OLS. Thus, quantile regression estimation goes beyond average effects and takes into account the heterogeneous effects of the covariate income at different parts of the well-being distribution. The quantile regression allows income effects to differ at different locations of the conditional distribution of well-being. The quantiles are cut points where a sample is divided into equal-sized, two or more subgroups. The 50th quantile is also the median value. The quantile regression estimates conditional quantile functions. In analogy with classical linear regression method which is based on minimising sums of squared residuals and meant to estimate models for conditional mean functions, the quantile regression method is based on minimising asymmetrically weighted absolute residuals and intends to estimate conditional median function and a full range of other conditional quantile functions. The quantile regression model, introduced by Koenker and Bassett (l978) as an extension of ordinary quantile, is a more general class of linear models in which the conditional quantiles have a linear form. The unconditional quantile regression estimation method, introduced by Firpo et al. (2009), is a way to estimate the differential effect on the unconditional quantiles of the outcome variable of a change in the distribution of a covariate.

Both conditional and unconditional quantile regressions are now widely used in the happiness literature (Binder & Coad, 2011; Yuan & Golpelwar, 2013; Fang & Sakellariou, 2015; Fang & Niimi, 2017). Binder and Coad (2011), using quantile regression on cross-sectional data, observe a decreasing effect of income on happiness distribution in the United Kingdom. Using the quantile regression, Yuan and Golpelwar (2013) study the differential impact of social and economic security, social inclusion, social cohesion and social empowerment on happiness distribution in China. Using the unconditional quantile regression, Fang and Sakellariou (2015) identify the determinants of less happy migrants in China. The quantile regression analysis has also been extended extensively to panel data (Geraci & Bottai, 2007; Abrevaya & Dahl, 2008; Lamarche, 2010). Canay (2011) studies the relationship between income and happiness applying the panel quantile regression method.

A large number of studies in happiness literature have so far analysed the determinants of happiness and its relationship with income. Most research in happiness economics revolves around the Easterlin Paradox, which portrays a paradoxical relationship between income and happiness. While Easterlin (1974; 2017) finds that at a particular point of time people with higher income are on average happier than people with lower income, the long-run effect of income on average happiness is almost nil, despite significant growth in income. However, Clark et al. (2008), Deaton (2008), Stevenson and Wolfers (2008) and Lakshmanasamy (2010) find a small positive and linear effect of income on happiness both in developed and developing countries. Empirical studies also observe that the income-happiness gradient is much smaller in developed countries than in developing countries (Blanchflower & Oswald, 2004; Clark et al., 2008; Clark & Senik, 2011; Diener et al., 2013; Clark, 2018). There also exists a satiation level of life satisfaction - after a threshold level in income, income increase has no effect on well-being (Layard, 2005; Hagerty & Veenhoven, 2003; Frey & Stutzer, 2002b).

This purpose of this paper is to estimate the differential effect of income on well-being using the quantile regression method. The paper uses the World Value Survey (WVS) data, the largest source of the cross-national panel survey in the world on subjective well-being, for India. The key question is, is the impact of income on well-being is uniform across the entire subjective well-being distribution? In other words, is the reaction of less satisfied people same as the reaction of highly satisfied people to changes in income? The use of panel data allows control of unobserved individual specific or state-specific heterogeneity. Empirically, this paper employs the panel quantile regression method in estimating the differential effect of the Net State Domestic Product (NSDP) per capita, a measure of average income, on individual and average subjective well-being indicators of life satisfaction and happiness across 12 states of India over 24 years from 1990 to 2014.

METHODOLOGY

To analyse the income-happiness relationship over the entire distribution of subjective well-being in India, this paper uses data from the World Value Survey (WVS). Since its beginning in 1981, six waves of WVS have been conducted between 1981 and 2014. The WVS is to understand the global changes in socio-cultural-political-religious values and beliefs. Additionally, the WVS also contains questions on subjective well-being and related aspects. The WVS uses a random probability sampling design and a face-to-face interview. The WVS covers close to 97 societies from all the six continents constituting 88 percent of world population, and the sixth wave (2014) includes 60 countries with more than 85,000 respondents. Being a part of the WVS, India has been surveyed since the second wave (1990) onwards. The WVS has started the survey in India in 14 major states with 2400 sample size, covering more than 90 percent of the nation's population and the sixth wave of WVS in India has been conducted in 22 states with a sample size of 4078 respondents. In total, there are more than 10,000 observations in the WVS of India. The empirical analysis of this paper uses all the 5 WVS waves data, consisting of 8,965 observations for 12 major states in India, for those states that are continuously sampled in each of the five waves of WVS over 24 years from 1990 to 2014. The 12 states are Andhra Pradesh (AP), Bihar (BI), Gujarat (GU), Karnataka (KAR), Kerala (KER), Madhya Pradesh (MP), Maharashtra (MR), Odisha (ODISHA), Rajasthan (RAJA), Tamil Nadu (TN), Uttar Pradesh (UP) and West Bengal (WB). The NSDP data of each state is drawn from the Reserve Bank of India *Handbook of Statistics on the Indian Economy*. The advantage of using panel data is that it allows control of unobserved individual-specific, wave specific and state-specific heterogeneity.

The WVS data provides information on the various indicators of subjective well-being. There are three main direct measures on overall SWB self-reported by the respondents themselves as their level of well-being on an ordered scale measure. The happiness question asks respondents to evaluate their present life in terms of "Taking all things together, would you say you are… very happy, quite happy, rather happy and not at all happy". The responses are recorded on a 4-point scale: very happy = 1, quite happy = 2, rather happy = 3, and not at all happy = 4. The life satisfaction question asks respondents for evaluation of whole life: "All things considered, how satisfied are you with your life as a whole are these days?" for which respondents self-select a value in a 10-point scale, starting with dissatisfied (=1) and ending with satisfied (=10). The question on satisfaction with the financial situation of the household asks: "How satisfied are you with the financial situation of your household?" and a 10-point response scale starts with completely dissatisfied (=1) and ends with completely satisfied (=10). For comparability and purpose of this paper, the happiness level is recoded reversely as not at all happy = 1, rather happy = 2, quite happy = 3, and very happy = 4.

In the happiness literature, life satisfaction and happiness indicators are treated as synonymous and used interchangeably as they mean and measure self-evaluation of life by the respondent himself. The ordinal nature of the measurement of subjective well-being indicators happiness and life satisfaction poses some methodological issue in the measurement of happiness. The categorical scales are not strictly cardinal and continuous, and assume equal distance between the ratings so that interpersonal comparison is possible. In happiness literature, empirical analyses consider the reported ordinal subjective well-being values as possessing some cardinal properties and, hence, treat the measures as continuous. Ferrer-i-Carbonell and Frijters (2004) test both cardinal and ordinal assumptions of happiness score and find that there is only a small difference in the estimated result of drivers of happiness, which is also supported by Frey and Stutzer (2002a). Clark et al. (2014) use an index of ordinal variation as a measure for ordinal variables for robustness check and obtain almost similar results. These results are in parallel with the view of Van Praag (1991) 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. In the happiness literature, the life satisfaction measure is considered to be a better measure for making cross-section comparison relative to the happiness measure (Di Tella & MacCulloch, 2006). The range of life satisfaction response scale is large (1-10) compared to the happiness scale (1-4) permitting greater choice and larger variations in reporting subjective well-being. The life satisfaction measure encompasses whole life, but happiness, being a feeling, may mean instantaneous or momentary gratification to respondents.

QUANTILE REGRESSION METHOD

The conventional linear regression equation is specified as,

$$yi = \beta xi + ui \tag{1}$$

where β is vector of unknown parameters associated with a change in the explanatory variable. The quantile regression model, as an extension of ordinary quantile, is a more general class of linear models in which the conditional quantiles have a linear form (Koenker & Bassett, l978). The quantile regression model is specified as,

$$y_i = \beta_q x_i + u_{qi} \quad q \in (0,1) \tag{2}$$

Consider a real valued random variable y characterised by the distribution function,

$$f(y) = \mathrm{P}(y \leq y_0) \tag{3}$$

The q^{th} quantile of y is defined as,

$$Q_q = \inf\,[y: f(y) \geq q] \tag{4}$$

Given a set of regressors, x_i, the quantile regression can be specified as,

$$f_q = (q - \beta_q x_i|x_i) = \mathrm{P}(y_i < q|x_i) \tag{5}$$

which is essentially a different form of equation (2) where the distribution of the error term u_{qi} is unspecified and the only constraint being the quantile restriction,

$$Q_q(u_{qi}|x_i) = 0 \tag{6}$$

The quantile regression is essentially non-parametric as no assumption is made about the conditional distribution of the dependent variable.

In contrast to the OLS and the maximum likelihood estimations, which are parametric and, therefore, need *a priori* distributional structure, the quantile regression uses linear programming methods in computation. To convert the regression problem into a linear programming problem, non-negative variables ε_i and v_i are introduced in the equation as,

$$y_i - \beta_{xi} + \varepsilon_i = 0 \quad i \in (i: y_i \geq \beta_{xi}) \tag{7}$$

$$\varepsilon_i = 0 i\forall(i: y_i \geq \beta_{xi}) \tag{8}$$

$$(\beta_{xi}) - y_i + v_i = 0 \quad i \in (i: y_i < \beta_{xi}) \tag{9}$$

$$v_i = 0 i\forall(i: y_i < \beta_{xi}) \tag{10}$$

Since ε_i and v_i are greater than the complementary sets, equations (7) and (9) can be rewritten as,

$$y_i = \beta_{xi} + \varepsilon_i - v_i = 0 \quad \varepsilon_i \geq 0, v_i \geq 0, i \in (1, n) \tag{11}$$

Thus, the linear regression problem with ε_i and v_i becomes a minimisation problem as,

$$min \sum_{i:y_i \geq \beta x_i}^{n} q\varepsilon_i + \sum_{i:y_i < \beta, x_i}^{n} (1-q)v_i \tag{12}$$

Note that ε_i and $v_i = 0$ $i\forall \in (1, n)$. Then,

$$\hat{\beta} = \frac{\sum_i^n (x_i - \ddot{x})(y_i - \ddot{y})}{\sum_i^n (x_i - \ddot{x})^2} \tag{13}$$

A significant departure of the quantile regression estimation from the linear regression estimation is that in quantile regression, the distance of points from a line is measured using a weighted sum of distances, where the weights are (1-q) for points below the fitted line and q for points above the fit line. While the OLS minimises the sum of the squares of the errors, $\sum u_i^2$, the quantile regression minimises $\sum q|u_i| + \sum(1-q)|u_i|$,, a sum that gives the asymmetric penalties $q|u_i|$ for under-prediction and (l-q) $|u_i|$ for over-prediction.

Thus, the standard conditional quantile is specified as a linear form,

$$Q_q(y_i|x_i) = \beta_q x_i \tag{14}$$

On substitution, the q^{th} quantile regression estimator $\hat{\beta}_q$ minimises over β_q the objective function,

$$Q(\beta_q) = \sum_{i:|y_i| \geq \beta x_i}^{n} q|y_i - \beta_q x_i| + \sum_{i:|y_i| \leq \beta x_i}^{n} (1-q)|y_i - \beta_q x_i| \quad (0<q<1) \tag{15}$$

where the first term is the actual value of yi higher than the predictor value and the second term is the actual value of y_i lower than the predictor value. If $L(u) = |u|$, the optimal predictor is the conditional median, $med(y|x)$, and the optimal predictor is that $\hat{\beta}$ minimises $\sum |y_i - x_i\beta|$. Therefore, the simple minimisation problem yielding the ordinary sample quantiles in the specific location model is the regression quantiles (Koenker and Bassett, 1978). Then, the q^{th} sample quantile is defined as any solution to the minimisation problem,

$$min \sum_{i:|y_i| \geq x_i\beta}^{n} q|y_i - x_i\beta_q| + \sum_{i:|y_i| < x_i\beta}^{n} (1-q)|y_i - x_i\beta_q| \quad (0<q<1) \tag{16}$$

Alternatively, the estimation of conditional mean function is specified as,

$$\hat{\beta} = \arg min_\beta \sum_{i=1}^{N} (y_i - \beta x_i)^2 \tag{17}$$

The linear conditional quantile function is specified as,

$$Q_y(q|x_i = x_0) = \beta_q x_i \tag{18}$$

which can be estimated by solving the equivalent of expression (14):

$$\hat{\beta}_q = \arg min_\beta \sum_{i=1}^{N} \gamma_q(y_i - \beta x_i) \tag{19}$$

where $\gamma_q(u)$ is the so-called check function defined as,

$$\gamma_q(u) = \begin{Bmatrix} qu & if\ u \geq 0 \\ (q-1)u & if\ u < 0 \end{Bmatrix} \tag{20}$$

Then, the expanded version of the quantile regression is specified as,

$$min_\beta \left[\sum_{i:y_i \geq \beta x_i} q|y_i - \beta x_i| + \sum_{i:y_i < \beta x_i} (1-q)|y_i - \beta x_i|\right] \tag{21}$$

which is equivalent to equations (12) or (16).

For the j^{th} regressor, the marginal effect is the coefficient for the q^{th} quantile,

$$\frac{\partial Q_q(y|x_i)}{\partial x_i} = \hat{\beta}_q \tag{22}$$

Thus, a quantile regression parameter β_q estimates the change at the specified quantile of the response variable y produced by a one-unit change in the independent variable x. The case of the median (q = 1/2) is the general result. Therefore, the quantile regression is also called median regression or least absolute deviation, as it minimises the sum of absolute residuals. Thus, quantile regression reveals information about the complete conditional distribution of the response variable without any constraints on the error term. Moreover, the estimation is robust to outliers of the response variable.

Following Firpo et al. (2009; 2018) and Fortin et al. (2011), the unconditional quantile regression can be specified as,

$$RIF(y;\ Q_q, \Phi_y) = Q_q + IF(y;\ Q_q, \Phi_y) = Q_q + \frac{q - I(y_i \leq q)}{\phi_y(Q_q)} = \beta_q x_i + u_{qi} \tag{23}$$

where expressions $\Phi_y(.)$ and $\phi_y(.)$ represent the density and probability distribution of y and $I(.)$ is the indicator function. The influence function $IF(y;\ Q_q, \Phi_y)$ represents the change in the distribution statistic Q_q due to the influence of individual observation. For the recentred influence function, RIF, the statistic $Q_q(\Phi_y)$ is added to the IF function, and the expectation of RIF is equal to $Q_q(\Phi_y)$. The first part of equation (23) is the RIF of the unconditional Q_q quantile of the dependent variable and the second part denotes the linear specification of the unconditional quantile regression. The conditional expectation of RIF,

$E[RIF(y;\, Q_q, \Phi_y)|x_i]$, is the unconditional quantile regression. Given the ceteris-paribus assumption, the OLS estimate of Q_q is treated as a consistent estimate of the marginal effect of change in the explanatory variable x on the unconditional quantile Q_q (Firpo et al., 2009; 2018; Fortin et al., 2011). Both the conditional and unconditional quantile regressions provide the picture of the change in the functional relationship between the distribution and its influencing factors when q moves from 0 to 1.

The panel quantile regression method controls for the individual heterogeneity in the panel. Canay (2011) suggests a simple two-step estimation procedure. In the first step, estimate the unobserved fixed effects using within estimators and in the second step, replacing the unadjusted independent variable by an adjusted one, estimate the conditional quantile regression. Specifically, the estimating quantile equation is specified as,

$$y_{it} = \beta_q x_{it} + \lambda_i + u_{it} \quad E(u_{it} \mid x_i, \lambda_i) = 0 \quad (24)$$

where y_{it} is the subjective well-being level of individual i at time t, x_{it} is a set of covariates including the main explanatory variable income, λ_i is the individual fixed effects and u_{it} is the error term.

According to Canay's (2011) two-step panel quantile estimation, the first step is to estimate the unobserved fixed effects,

$$\hat{\lambda}_i = E_T[y_{it} - \hat{\beta}_q x_{it}] \quad (25)$$

where $\hat{\beta}_q$ is a $\sqrt{nT}$ consistent estimator of β_q estimated from the within regression model (Fang and Niimi, 2017). The second step is to estimate,

$$\hat{\beta}_q = arg \min_{\beta \in R^k} E_{nT}[\rho_q\,(\hat{y}_{it} - q x_{it})] \quad (26)$$

where $\hat{y}_{it} = (y_{it} - \hat{\lambda}_i)$ (27)

The Canay's (2011) two-step estimator is consistent as well as normally distributed, and hence, as the Monte Carlo simulations suggest, it is very close to Koenker's (2004) estimator. This two-step quantile estimation is widely applied in happiness studies (Binder, 2015; Binder & Coad, 2015; Fang, 2015). This paper also applies Canay's (2011) estimation method to analyse the distributional effects of income on life satisfaction distribution, controlling for unobserved individual heterogeneity.

RESULTS AND DISCUSSION

Table 1 presents the growth rate of NSDP in the 12 states in India during the period 1990-2014. The growth rate of combined NSDP of all the 12 states together has increased from 5.51 percent to 7.14 percent during the 1990-2015 period, almost close to the picture of GDP growth of India. At the state level, growth has accelerated sharply in all states, except Karnataka. The states with the growth rate below the national growth rate during the first period 1990-91 to 1999-2000 have registered faster growth rate in the third period 2010-11 to 2014-15. Especially, the growth has been spectacular in the laggard states Bihar (2.85 to 11.03), Madhya Pradesh, Rajasthan and Uttar Pradesh. In Madhya Pradesh and Tamil Nadu growth rate has declined in the second period and rebounded in the third period. In Andhra Pradesh, Gujarat, Karnataka, Kerala and West Bengal growth has declined in the third period between 2000-01 to 2009-10 and 2010-11 to 2014-15, whereas Bihar, Madhya Pradesh, Maharashtra, Rajasthan, Tamil Nadu and Uttar Pradesh experienced accelerated growth in this period. Thus, there has been contrasting growth performance and significant variations across states of India over time. As the coefficient of variation reveals, the degree of dispersion has declined in the second period, from 0.28 to 0.18, but increased in the third period, to 0.24. Thus, the acceleration of growth is evident not just for aggregate GDP, but even more strongly for individual states.

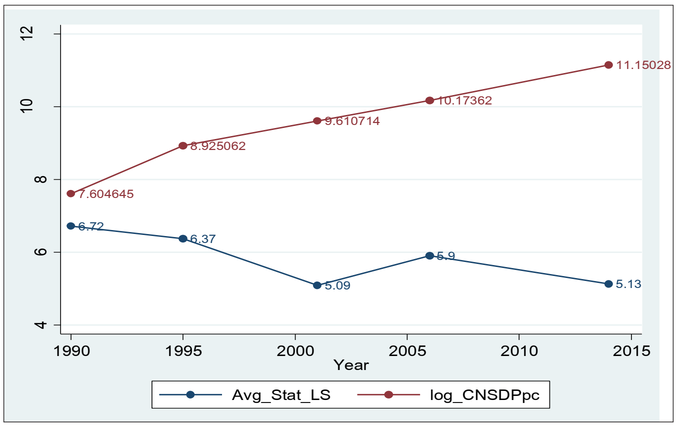
Table 1: Average Annual Growth Rate of NSDP in States of India, 1990-2014

(percent per year)

State	1990-91 to 1999-2000	2000-01 to 2009-10	2010-11 to 2014-15	State	1990-91 to 1999-2000	2000-01 to 2009-10	2010-11 to 2014-15
AP	5.2	7.59	5.56	Rajasthan	6.55	6.86	8.13
Bihar	2.85	8.65	11.03	Tamil Nadu	6.32	5.31	7.75
Gujarat	6.8	8.91	7.88	UP	3.59	5.32	5.92
Karnataka	6.75	7.59	6.66	West Bengal	6.67	7.20	6.28
Kerala	5.99	7.79	6.15	Combined NSDP	5.51	7.06	7.14
MP	6.16	5.10	8.55	India GDP	5.83	7.21	6.86
Maharashtra	6.61	6.86	7.33	CV	0.28	0.18	0.24
Odisha	2.68	7.61	4.44				

Sources: Directorate of Economics & Statistics of respective states and CSO India series.

Though India and its states are growing at the economic ladder, the well-being of Indians is not improving correspondingly. The World Happiness Index (2018) of the United Nations places India at the 133rd rank among 156 countries in the world, a drop of 11 ranks from the 2017 rank, in which India stands low to its less developed neighbours. India's rank in the World Happiness Index is decreasing over the last few years. In 2013, it was 111st, 117th in 2015, 118th in 2016 and 122nd in 2017, with a continuous fall in the scores also. The World Value Survey also reveals that happiness and life satisfaction are not in tandem with economic growth in India. Fig. 1 shows that the average life satisfaction has declined with an increase in average per capita NSDP across states in India. The mean life satisfaction level across all states is 5.80 and the mean of log NSDP per capital is 8.97. While there is 35 times increment in the growth rate of NSDP per capita during 1990-2014, the average life satisfaction per state has declined by around 1 percent over this period. Thus, the average well-being is not moving in the same direction and the same speed with income.



Sources: Data on life satisfaction from WVS (1990-2014), and data on NSDP from RBI: Handbook of Statistics on the Indian Economy, 2016-2017.

Fig. 1: Growth of Average Life Satisfaction and NSDP Per Capita in States of India, 1990-2014

Not only the average life satisfaction in the states of India has declined, but also there are significant variations in well-being across the states and among people within states. The average subjective well-being levels in the 12 states of India, presented in Table 2, show that out of 12 states, 8 achieved a mean score of life satisfaction above the national average of 5.94. The mean life satisfaction score is higher (6.79) in Tamil Nadu, while for people of West Bengal the score is only 4.83. In West Bengal, only 6 percent report complete life satisfaction while 15.10 percent report complete dissatisfaction with life. Surprisingly, in the economically poor states, Madhya Pradesh, Rajasthan and Uttar Pradesh, the average life satisfaction score is comparatively higher. The distribution of happiness level indicates that 5 states achieve mean happiness level above the national average of 2.99. More than 41 percent people in Odisha and Gujarat express that they are very happy with their current life, but only a lower percentage of people in Andhra Pradesh, Kerala and West Bengal report happiness in life.

Table 2: Average Subjective Well-being Across States of India, 1990-2014

State	Mean Life Satisfaction	Mean Happiness	Mean Financial Satisfaction
Andhra Pradesh	6.14 (2.40)	2.92 (0.66)	5.68 (2.31)
Bihar	5.89 (2.36)	2.86 (0.85)	5.43 (2.42)
Karnataka	5.26 (2.20)	2.84 (0.79)	4.93 (2.18)
Kerala	5.97 (2.35)	2.92 (0.72)	5.41 (2.23)
Madhya Pradesh	6.22 (2.21)	3.07 (0.74)	5.87 (2.11)
Maharashtra	5.73 (2.52)	2.95 (0.88)	5.56 (2.45)
Odisha	5.97 (2.56)	3.21(0.78)	5.33 (2.52)
Rajasthan	6.13 (2.57)	3.25 (0.69)	5.18 (2.40)
Tamil Nadu	6.79 (2.13)	3.16 (0.78)	6.76 (2.20)
Uttar Pradesh	6.07 (2.67)	2.90 (0.84)	5.52 (2.60)
West Bengal	4.83 (2.55)	2.89 (0.74)	4.91 (2.29)
Pearson's chi2	980.61	496.90	890.76

Note: Standard deviations in parentheses.

The distribution of average life satisfaction and happiness levels among low and high- income groups in the states in 2014, the sixth wave of WVS in India, in Table 3 also shows that in 7 of 12 states, the mean happiness score for higher-income groups is greater than that for lower-income groups. In most states, the average life satisfaction level is higher for low-income groups and lower for high-income groups, but Bihar reports a lower level of average life satisfaction for higher-income groups than that of lower-income groups.

Table 3: Average Subjective Well-being among Low and High-Income Groups in India, 2014

State	Mean Life Satisfaction			Mean Happiness		
	Low-Income Group	High-Income Group	Chi^2 Value	Low-Income Group	High-Income Group	Chi^2 Value
Andhra Pradesh	4.78 (2.57)	2.85 (1.77)	5.05	3.11 (0.86)	3.16 (0.41)	6.41*
Bihar	5.2 (1.42)	3.90 (1.65)	9.24*	2.1 (1.02)	3.0 (0.31)	5.20
Gujarat	4.6 (3.21)	7.32 (2.71)	23.13***	2.88 (0.93)	3.6 (0.71)	10.14**
Karnataka	5.4 (2.27)	5.44 (2.40)	3.28	3.6 (0.5)	3.40 (0.50)	1.92
Kerala	4.55 (2.70)	-	-	2.55 (0.90)	-	-

State	Mean Life Satisfaction			Mean Happiness		
	Low-Income Group	High-Income Group	Chi^2 Value	Low-Income Group	High-Income Group	Chi^2 Value
Madhya Pradesh	6.0 (2.60)	5.71 (3.38)	6.95	3.35 (0.84)	3.57 (0.75)	5.52
Maharashtra	3.60 (2.27)	3.50 (2.08)	9.24	2.85 (1.06)	3.07 (0.83)	5.57
Odisha	6.8 (0.78)	5.75 (1.70)	6.81	3.5 (0.70)	3.75 (0.50)	0.52
Rajasthan	2.46 (1.11)	-	-	3.60 (0.49)	-	-
Tamil Nadu	8.5 (0.71)	6.35 (2.05)	4.02	3.5 (0.70)	2.5 (1.08)	1.82
Uttar Pradesh	6.14 (3.08)	8.02 (2.16)	29.44***	3.12 (0.73)	3.35 (0.51)	6.48*
West Bengal	5.6 (2.38)	5.88 (2.52)	10.82*	3.46 (0.51)	3.44 (0.52)	0.01

Note: Standard errors in parentheses. - No observations.

The distribution of subjective well-being levels within and across the 12 states of India, reported in Table 4, also reveal significant differences in the distribution of life satisfaction and happiness levels across states, as the respective significant Pearson's chi-square value of 980.61 and 496.90 indicates.

Table 4: Distribution of Subjective Well-being Levels Across States in India, 1990-2014

State	Dissatisfied	5^{th} Level	Satisfied	Mean LS*	Not Happy	Rather Happy	Quite Happy	Very Happy	Mean*
AP	41(5.42)	210(27.74)	75(9.91)	6.14(2.40)	13(1.72)	157 (20.77)	462 (61.11)	124(16.40)	2.92(0.66)
Bihar	21(2.38)	247(27.97)	106(12.00)	5.89(2.36)	52(5.70)	245 (26.86)	389 (42.65)	226(24.78)	2.86(0.85)
Gujarat	35(6.82)	92(17.93)	96(18.71)	6.31(2.75)	11(2.14)	90(17.48)	201 (39.03)	213(41.36)	3.19(0.79)
Karnataka	14(2.61)	184(34.33)	42(7.84)	5.26(2.20)	14(2.65)	169(31.95)	23243.86)	114(21.55)	2.84(0.79)
Kerala	9(2.54)	88(24.86)	52(14.69)	5.97(2.35)	15(4.24)	61(17.23)	212(59.89)	66(18.64)	2.92 (0.72)
MP	30(4.55)	155(23.52)	48(7.28)	6.22(2.21)	11(1.55)	134(18.93)	355(50.14)	208(29.38)	3.07(0.74)
Maharashtra	81(7.53)	297(27.63)	99(9.21)	5.73(2.52)	61(5.64)	265(24.51)	420(38.85)	335(30.99)	2.95(0.88)
Odisha	29(7.73)	103(27.47)	53(14.13)	5.97(2.56)	5(1.33)	66(17.51)	148(39.26)	158(41.91)	3.21(0.78)
Rajasthan	23(4.60)	123(24.60)	82(16.40)	6.13(2.57)	11 (2.10)	43(8.22)	271(51.82)	198(37.86)	3.25(0.69)
Tamil Nadu	12(1.63)	150(20.35)	108(14.65)	6.79(2.13)	304.05)	83(11.20)	366(49.39)	262(35.36)	3.16(0.78)
Uttar Pradesh	87(5.42)	364(22.67)	265(16.50)	6.07(2.67)	86(5.27)	401(24.56)	724(44.34)	422(25.84)	2.90(0.84)
West Bengal	114(15.10)	212(28.08)	48(6.36)	4.83(2.55)	36(4.77)	144(19.10)	439(58.22)	135(17.90)	2.89(0.74)
Pearson chi^2	980.61 (Prob. = 0.00)				496.90 (Prob. = 0.00)				

Note: Percentage figures in parentheses. * Standard deviation in parentheses.

The changes in well-being across states over time in the 12 states of India between 1990 and 2014 are presented in Table 5. It is observed that most states, except three states, experienced a decline in life satisfaction over the 24 years. The mean score of the combined life satisfaction of all the 12 states decreased from 6.57, in 1990, to 5.16, in 2014. Two states, Karnataka and Madhya Pradesh, experienced a modest gain in average life satisfaction; in West Bengal, the score remained the same at 6.01. Among the states that experienced a decline in average life satisfaction, Rajasthan (-4.22) records the highest decline while Uttar Pradesh (-0.19) records the lowest percentage change in mean life satisfaction. Table 5 further reveals that the average happiness of all 12 states taken together slightly increased from 2.92 to 3.11, about 0.26 percentage gain over the 24 years between 1990 and 2014 in Indian states. During this period, eight states experienced a modest rise in mean happiness. But, in four states, the mean happiness declined over time. These states are Bihar (-0.38), Kerala (-0.57), Maharashtra (-0.14) and Tamil Nadu (-0.97). Among the states where mean happiness increased over time, Karnataka scores the highest percentage increase in mean happiness (1.59), Gujarat (0.05) has experienced the lowest increase in mean happiness.

Table 5: Changes in Average Subjective Well-being across States - Over Time in India, 1990-2014

State	Life Satisfaction			Happiness		
	Mean LS (1990)	Mean LS (2014)	Percent Change	Mean Happiness (1990)	Mean Happiness (2014)	Percent Change
Andhra Pradesh	6.53 (2.15)	4.78 (2.69)	-1.29	2.82 (0.67)	2.96 (0.83)	0.20
Bihar	6.83 (2.27)	4.81 (1.77)	-1.45	2.87 (0.94)	2.62 (0.79)	-0.38
Gujarat	6.74 (2.01)	5.44 (3.13)	-0.89	3.19 (0.67)	3.23 (0.82)	0.05
Karnataka	5.35 (1.90)	5.39 (2.35)	0.03	2.47 (0.65)	3.61 (0.49)	1.59
Kerala	7.46 (2.26)	4.34 (2.66)	-2.23	2.96 (0.70)	2.6 (0.92)	-0.54
Madhya Pradesh	6.25 (2.40)	6.98 (1.97)	0.46	2.95 (0.85)	3.46 (0.58)	0.67
Maharashtra	6.68 (2.13)	3.45 (2.14)	-2.72	2.93 (0.78)	2.83 (0.99)	-0.14
Odisha	7.27 (2.32)	5.47 (1.38)	-1.18	3.12 (0.73)	3.75 (0.49)	0.77
Rajasthan	6.94 (2.22)	2.46 (1.12)	-4.22	3.05 (0.71)	3.61 (0.49)	0.71
Tamil Nadu	7.98 (1.29)	6.07 (1.89)	-1.13	3.32 (0.65)	2.63 (1.05)	-0.97
Uttar Pradesh	6.69 (2.52)	6.37 (3.08)	-0.19	2.89 (0.79)	3.15 (0.71)	0.36
West Bengal	6.01 (2.30)	6.01 (2.37)	0	2.71 (0.73)	3.3 (0.53)	0.82
Overall	6.57 (2.28)	5.16 (2.74)	-1.00	2.92 (0.79)	3.11 (0.85)	0.26

Note: Standard errors in parentheses.

Table 6 presents the distribution of subjective well-being at the group level. The 12 states are grouped into three broad categories based on the state NSDPpc (Mukherjee et al., 2016): developed states (NSDPpc higher than the second quartile or median), developing states (NSDPpc in between the first and the second quartile) and less-developed states (NSDPpc less than the first quartile). Interestingly, the less-developed states have a higher percentage (15.25 percent) of people who report that they are satisfied with their life. In developed states, 12 percent report satisfaction with life and, in the developing states, less than 10 percent are satisfied with their life. This result is reflected in the mean score of life satisfaction in each group of states also. The mean life satisfaction score for less-developing states is 6.03, while the mean score of developed states is 5.97 and developing states is 5.74. In terms of happiness level, about 28 percent of people in all states report that they are very happy with life. In less-developed states, a higher proportion, 5 percent, compared to only 1 percent in developing states, report unhappiness with their current life. Comparisons of mean scores of happiness for these states reveal that developing states have a higher average score of happiness (3.10), the mean happiness is 2.97 in developed states and 2.91 in less-developed states. Overall, people in less-developed states are more satisfied with life than people in developing states, while happiness is relatively high in both developed as well as less-developed states.

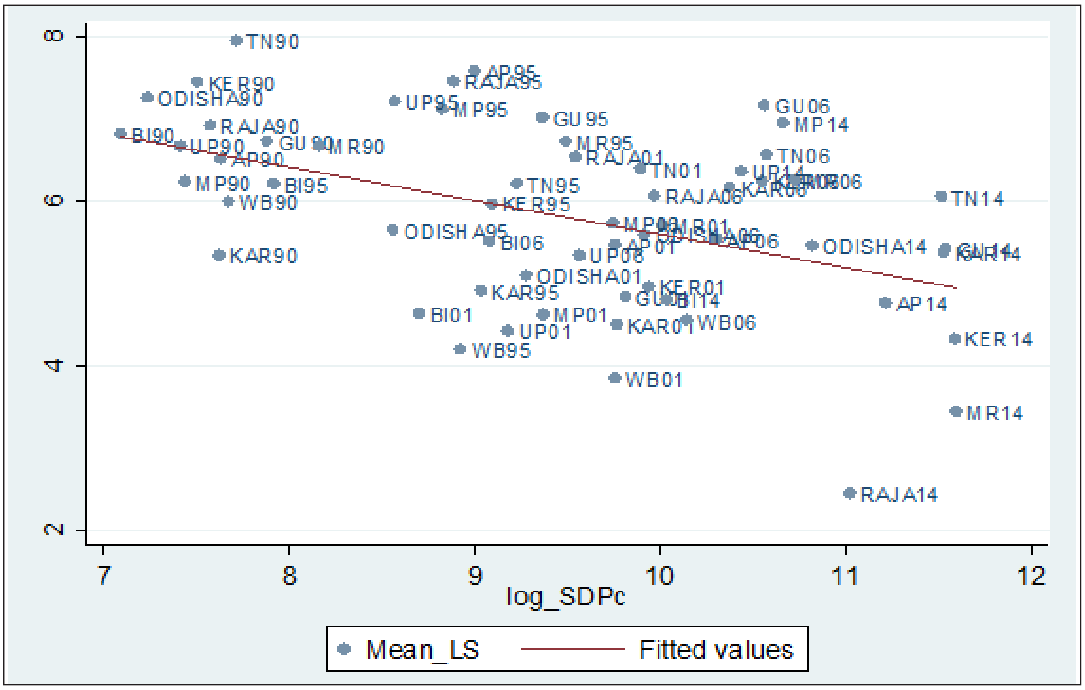
Table 6: Distribution of Subjective Well-being Indicators across Developed, Developing and Less-Developed States of India, 1990-2014

Life Satisfaction				
State	Dissatisfied	5th Level	Satisfied	Mean LS*
Developed	241(6.06)	946(23.77)	469 (11.79)	5.97 (2.53)
Developing	130(6.43)	633(31.29)	192(9.49)	5.74 (2.39)
Less-Developed	124(4.61)	645(24.00)	410(15.25)	6.03 (2.59)
	Pearson chi 2 = 223.78 Prob. = 0.000			

Happiness					
State	Not at all Happy	Rather Happy	Quite Happy	Very Happy	Mean*
Developed	173 (4.33)	864(21.65)	1,835(45.98)	1,119(28.04)	2.97 (0.82)
Developing	31 (1.49)	319(15.29)	1,144(54.82)	593 (28.41)	3.10 (0.69)
Less-Developed	141 (5.14)	673 24.52)	1,202(43.79)	729 (26.56)	2.91(0.84)
	Pearson chi^2 = 144.09 Prob. = 0.000				

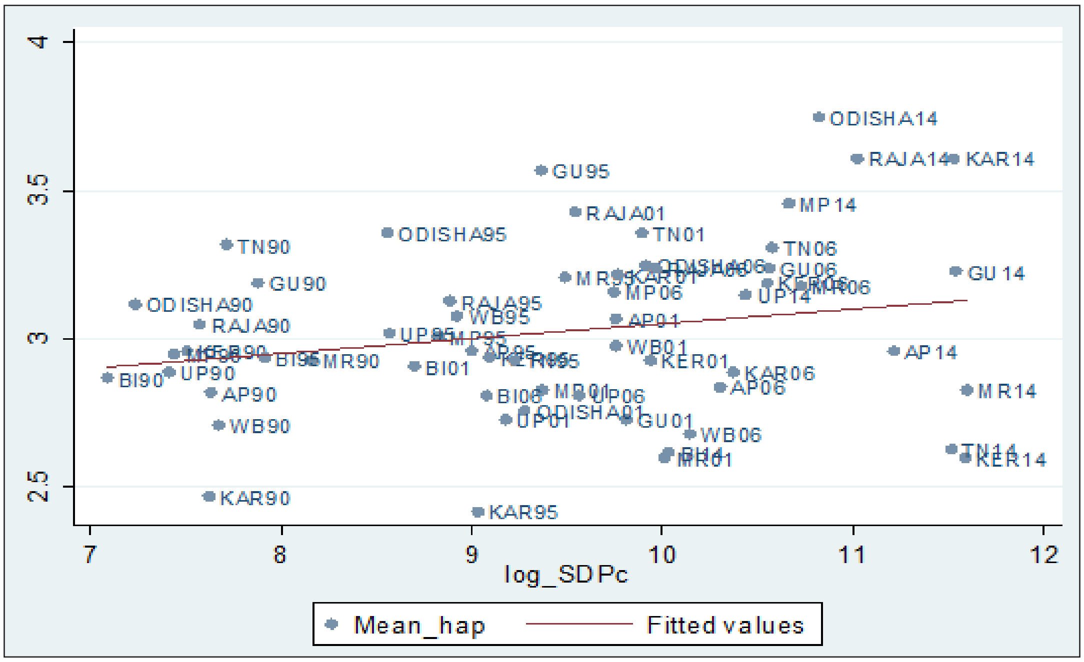
Note: Percentage figures in parentheses. * Standard deviations in parentheses.

Figs. 2 and 3 present the relative, subjective well-being levels of each of the states across all waves vis-a-vis income growth. From Fig. 2, it can be inferred that there is a negative relationship between life satisfaction and log NSDP per capita over time i.e. economic growth is accompanied by a decline in life satisfaction. While all the 12 states experienced significant growth in NSDP between 1990 and 2014, they also experienced a decline in life satisfaction, except two states Karnataka and Madhya Pradesh. The average life satisfaction across the states has declined was 6.57, in 1990, to 5.16, in 2014. But in contrast to the long-term relationship of life satisfaction with log per capita NSDP, the average state-level happiness is moving upward with the rise in per capita NSDP over time (Fig. 3).



Note: Each state is labelled as 90, 95, 01, 06 and 14 indicating the state WVS waves respectively.

Fig. 2: Relationship between NSDP Per Capita and Life Satisfaction across States - Over Time in India, 1990-2014



Note: Each state is labelled as 90, 95, 01, 06 and 14 indicating the state WVS waves respectively.

Fig. 3: Relationship between NSDP Per Capita and Happiness across States - Over Time in India, 1990-2014

Figs. 4 and 5 present the relationship between changes in subjective well-being and log real NSDP per capita over the 24 years for all states. It can be observed that changes in both life satisfaction and happiness are not in tune with positive changes in economic growth. A larger rise in NSDP per capita is not associated with any marked increase in well-being in Indian states. The fitted line of the relationship between changes in life satisfaction and per capita NSDP over 1990 and 2014 in Fig. 4 falls below the -1 percent change, indicating that life satisfaction levels declined in Indian states. Only Madhya Pradesh has increased life satisfaction slightly while life satisfaction in Karnataka has remained the same despite a vast increase in income per capita. Even with a higher percentage increase in income, Kerala and Rajasthan experienced a drastic decline in life satisfaction. The fitted line in Fig. 5 between percentage changes in happiness and economic growth over time is slightly above the 0-change and almost horizontal with a slight downward slope. Though the annual change in happiness is positively related to economic growth in half of the states, more than twenty years of significant growth of per capita NSDP does not make the people happier. The only state which gains a better improvement is Karnataka, while Madhya Pradesh, Rajasthan and Odisha gain modestly. With higher per capita NSDP growth, Tamil Nadu and Kerala experienced more reduction in the happiness level of their people.

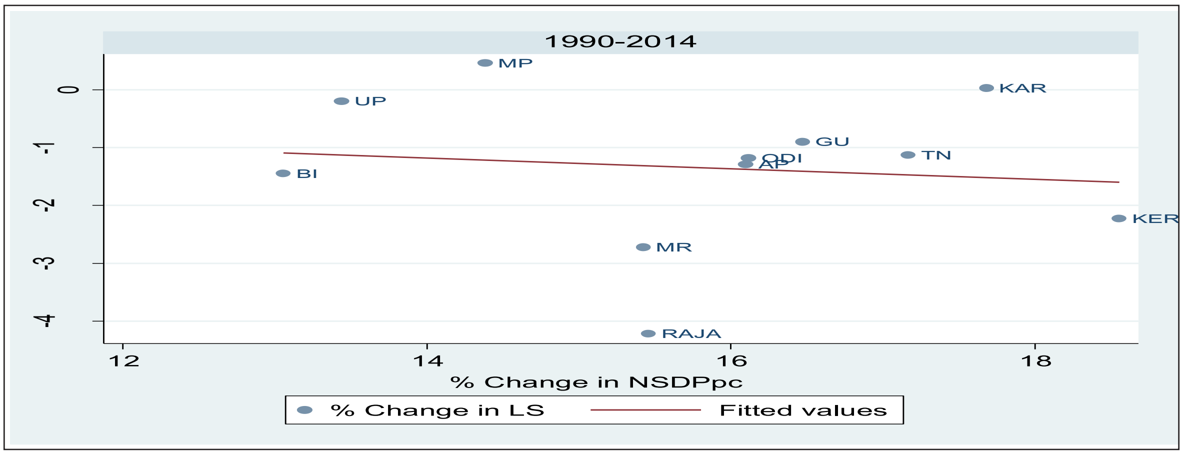


Fig. 4: Relationship between Changes in NSDP Per Capita and Life Satisfaction across States - Over Time in India, 1990-2014

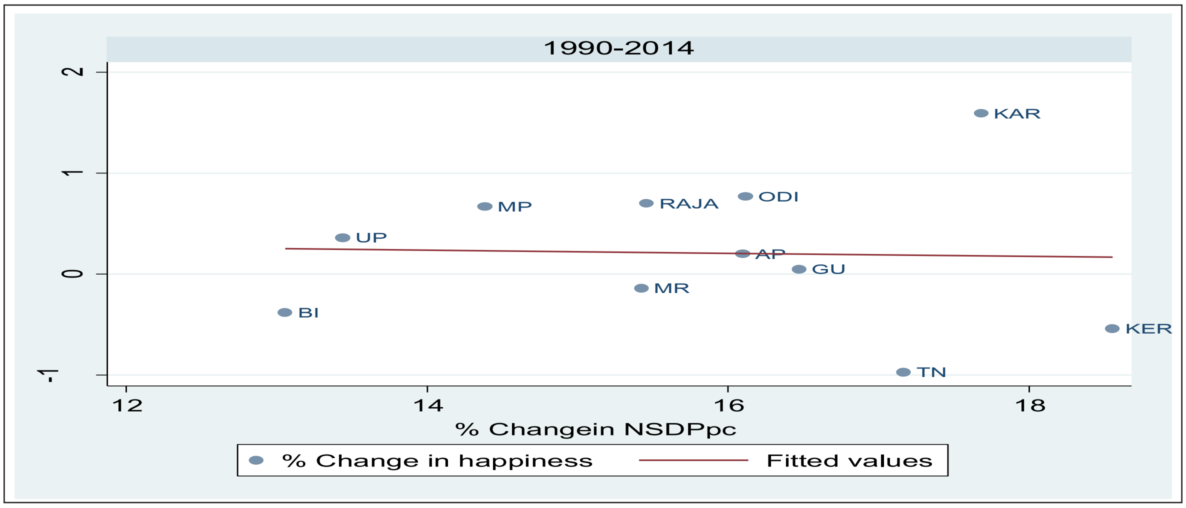


Fig. 5: Relationship between Changes in NSDP Per Capita and Happiness across States - Over Time in India, 1990-2014

Thus, from the distribution of average and changes in subjective well-being levels within and across states and income groups, it can be observed that life satisfaction and happiness levels are not the same for everyone at the aggregate level. There exists ample indication to presume that the response of subjective well-being indicators to changes in income is heterogeneous across the well-being distribution. Therefore, the differential income effects at different points of well-being distribution, the 10th, 25th, 50th, 75th and 90th quantiles, are estimated by the quantile regression method. To compare the quantile effects from the average effects, the OLS and ordered probit estimates are also reported.

Table 7 presents the panel quantile regression estimates of the log of NSDP per capita income on individual subjective well-being (life satisfaction and happiness) levels. It is observed from the coefficient estimates of the income, both the average and the quantiles, on individual subjective well-being is negative and statistically highly significant. But, the income effect varies across the quantiles. As observed from the income-life satisfaction distribution across-states over-time, an increase in NSDP per capita income decreases individual life satisfaction level. The OLS estimate shows that on average life satisfaction decreases by 39 percent with an increase in NSDP per capita. The ordered probit estimates also reveal that the probability of reporting higher levels of life satisfaction falls by almost 17 percent as average income increases. But, for the dissatisfied people, those at the bottom 10th quantile of the life satisfaction distribution, an increase in per capita state income reduces life satisfaction by nearly 58 percent, relatively higher than the average income effect. But, at the 90th quantile i.e. for the highly satisfied people, income growth has zero impact on life satisfaction. At the median 50th and 75th quantiles, the income effect on life satisfaction is lesser than the less satisfied people but slightly higher than the 25th quantile.

Table 7: Panel Quantile Regression Estimates of Individual Subjective Well-being in States of India, 1990-2014

Variable	OLS	Ordered Probit	q10	q25	q50	q75	q90
Individual Life Satisfaction			**At quantiles**				
lnNSDPpc	-0.390*** (0.007)	-0.170*** (0.009)	-0.575*** (0.027)	-0.383*** (0.019)	-0.472*** (0.016)	-0.455*** (0.024)	0.000*** (0.000)
lnNSDPpc with state-fixed effects	-0.512*** (0.005)	-0.208*** (0.009)	-0.629*** (0.006)	-0.496*** (0.013)	-0.420*** (0.011)	-0.497*** (0.006)	0.000*** (0.000)
Individual Happiness			**At Quantiles**				
			q10	**q25**	**q50**	**q75**	**q90**
lnNSDPpc	0.042*** (0.002)	0.059*** (0.009)	4.37*** (0.018)	5.94*** (0.021)	0.391*** (0.020)	0.315 (0.364)	-0.035 (0.100)
lnNSDPpc with state-fixed effects	0.050* (0.028)	0.052*** (0.010)	0.005 (0.438)	-0.0002 (0.041)	0.000 (0.002)	0.000 (0.015)	-0.035*** (0.004)

Note: Robust standard errors in parentheses. *** and * indicate significance level respectively at 1 and 10 percent. Controls in both specifications include age, gender, education, marital status, employment status, health status, religion and socio-economic status. Control coefficients and model fitting not reported for brevity.

With controls for state-fixed effects, the negative income effect increases both at the average level and all the quantiles also. While the average income effect is a negative 50 percent on life satisfaction, the probability of achieving higher levels of life satisfaction falls by 21 percent. The decline in the income effect at different quantiles holds at the aggregate level also. While the income effect is a strong negative 64 percent for those at the bottom of the life satisfaction distribution, for those highly satisfied people, the marginal income change does not matter for satisfaction. Thus, the quantile regression estimates of life satisfaction identify a monotonic decrease in individual life satisfaction with an increase in average income across the quantiles.

The coefficient estimates for happiness reported in Table 7 reveal a different picture. In contrast to the individual life satisfaction estimates, the income effect on happiness is significantly positive, both at the average level and at the quantiles. While the average income effect is 4 percent, the probability of higher happiness increases by 6 percent. However, the effect of an increase in average income on individual happiness is strong up to the median quantile, but at the higher quantiles, increase in average income has no statistical effect on the happiness level of individuals. When state-fixed effects are controlled, at the individual level, the average income effect becomes weakly negative; but, the probability of reporting higher levels of happiness is still a significant positive 5 percent. But, the income effect is almost zero and insignificant at most quantiles, except the 90th quantile. For those individuals at the higher end of happiness distribution, the effect of NSDP per capita is a significant mild decrease in happiness. This implies that an increase in average income reduces the happiness by 3 percent for the very happy people as compared to a 5 percent increase in happiness of the unhappy people.

At the aggregate states-level estimation, the average income–well-being relationship at the quantiles is somewhat mixed. From Table 8, it is observed that there is no monotonic decrease in the impact of average income on life satisfaction distribution across the quantiles. On average, an increase in NSDP per capita reduces average life satisfaction in the states of India by 42 percent. But, for a person belonging to the less satisfied category, increase income average income reduces life satisfaction more than 100 percent and for the highly satisfied people the decline is about 25 percent. In the middle quantiles, at the 25th quantile, the average life satisfaction of the state increases more than 100 percent, but at the median quantile, the response again decreases by 37 percent before turning to a positive 45 percent gain. But the estimated effects controlling for state-fixed effects show consistently negative response of life satisfaction for average income on average as well as at all the quantiles. All the estimated coefficients are significantly negative. The average income effect on life satisfaction is a relatively higher 50 percent; but at lower quantiles, the income effect is almost halved to the uncontrolled effects. At the higher satisfaction level, 90th quantile, though income effect is a mild positive 2 percent, it is statistically insignificant.

Table 8: Panel Quantile Regression Estimates of Average Subjective Well-being in States of India, 1990-2014

Variable	OLS	Average Life Satisfaction				
		q10	**q25**	**q50**	**q75**	**q90**
lnNSDPpc	-0.418***	-1.17***	1.22***	-0.370***	0.450	-0.248**
	(0.007)	(0.269)	(0.283)	(0.0007)	(0.683)	(0.101)
lnNSDPpc with state-fixed effects	-0.504***	-0.285***	-0.486***	-0.621***	-0.543***	0.020
	(0.008)	(0.016)	(0.011)	(0.007)	(0.126)	(0.023)
		Average Happiness				
		q10	**Q25**	**q50**	**q75**	**q90**
lnNSDPpc	0.042***	9.96***	-0.017	0.100***	0.114***	-2.10
	(0.002)	(0.004)	(0.024)	(0.005)	(0.037)	(2.27)
lnNSDPpc with state-fixed effects	0.036***	-0.062***	-0.012***	0.024***	0.166***	0.112***
	(0.002)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)

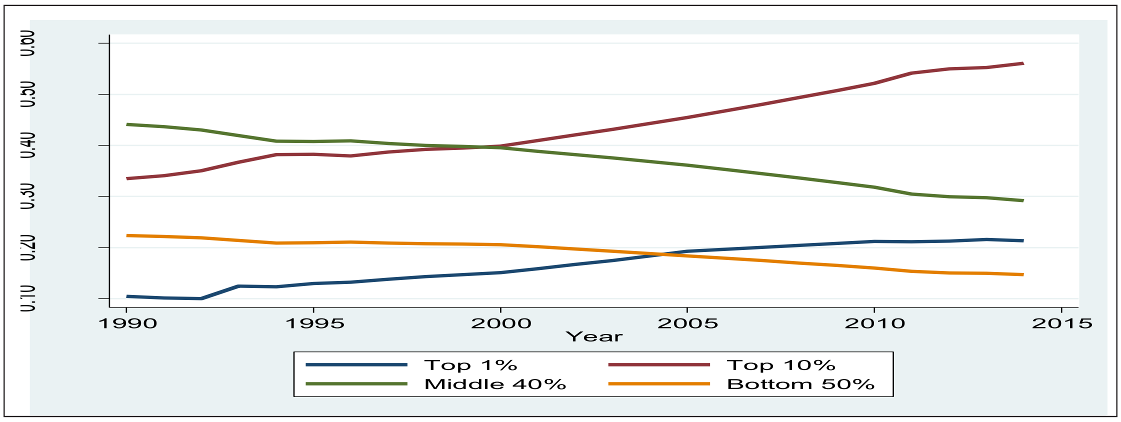
Note: Robust standard errors in parentheses. ***, **, * indicate level of significance respectively at 1, 5 and 10 percent. Model fitting not reported for brevity.

The average income effect on happiness is a significant positive 4 percent. However, the quantile effects are in contrast with and without controls for state-fixed effects. In the without control estimates, for the less happy people, happiness level increases by nearly doubles with an increase in average income; but for the very happy people, a rise in average income reduces their happiness level more than 200 percent. However, controlling for state-fixed effects reverses the result, for the unhappy people, as average income increases, the happiness level decreases by 6 percent and for the happy people, the happiness level significantly 11 percent with a rise in average income. At the 25th quantile, the estimated income effect is a mild negative and at the median and 75th quantiles, an increase in average state income has a significant positive impact on the happiness level. Thus, the estimated quantile results are in line with the empirical findings on the Easterlin paradox in cross-country studies. A rise in average income means a rise in everyone's income and as everyone's income increases, the relative status of an individual remains the same and, hence, no positive impact or reduction in life satisfaction even when income increase is substantial. The contrasting response of happiness at different quantiles to the increase in average income may be due to the narrow range of the 4-point happiness scale.

The empirical results of this paper are in line with the more recent evidence for the United States (Easterlin, 2017; Graham, 2017). With increase in average income, more and more people feel less happy and dissatisfied. This is in stark contrast to the earlier findings by Easterlin (1974) that within country rich people appear to be more happy; but across countries and over time, there is no direct income-happiness relationship at the average level. Consistent with Graham's (2017) findings for the United States, the WVS Indian data also shows that in the long-run life satisfaction is not increasing with income growth. Kahneman et al. (2006) find that within-countries analysis may be biased in estimating the true relationship between country life satisfaction and income due to the idea of "focusing illusion": the life satisfaction question allows people to evaluate their life by comparing themselves with others, then they kingpin their position relative to others considering the measure of income. Although this bias has a significant impact on within-countries comparisons, it seems likely that cross-countries relationship between subjective well-being and GDP may also demonstrate the influence of other important factors. Stevenson and Wolfers (2008) note that "other factors such as increased savings, reduced leisure, or even increasingly materialist values, may raise GDP per capita at the expense of subjective well-being" (p. 35). Many of these factors may rise or pull both GDP per capita and subjective well-being.

Among the lists of suspected factors that may absorb the benefits of economic growth and adversely affect the life satisfaction of a country, income inequality and declining social capital play significant roles. Chancel and Pickety (2019) observe worsening income inequality in India, which may dent the gains of rapid economic growth and its share among the different populations of India. The International Monetary Fund (2016) observes that India's Gini coefficient rose to 0.51, in 2013, from 0.45, in 1990. The gap in income share between the richest 10 percent and poorest 40 percent of the population in India has been on a constant increase from 1995, and the benefits of growth have increasingly accrued to the richest members of society, pushing income inequality ever higher. This is evident from the rate of increase in the number of billionaires in India, which has been the fastest compared to other Asian countries. The World Bank Report on Inequality in South Asia (2012) states that the total billionaire wealth represents about 12 percent of the GDP of India in 2012. Graham (2017) gives a more psychological explanation for this phenomenon. She argues that with rising income inequality when income grows, different sections of the society fall apart, people suffer more pain and stress, feel less optimistic, lack hope and loss of confidence and the mental well-being of people becomes unequal which lowers life satisfaction.

Fig. 6 shows that the income share of the bottom 40-50 percent population has declined drastically while that of the top 1-10 percent has increased sharply in India between 1990 and 2014. However, as Fig. 7 shows the average life satisfaction of top income group is flat, though high. Also, the average life satisfaction of bottom income group is flat but low. Importantly, there has been a significant decline in life satisfaction of the middle-income groups. The income increase has not impacted much the subjective well-being levels both at the lower and upper satisfaction levels and among the bottom and top income groups in India. The people in the middle income groups and with the average levels of life satisfaction have not gained any increase in their subjective well-being from income growth in India.



Source: World Inequality Database (2017).

Fig. 6: Share in National Income by Income Groups in India

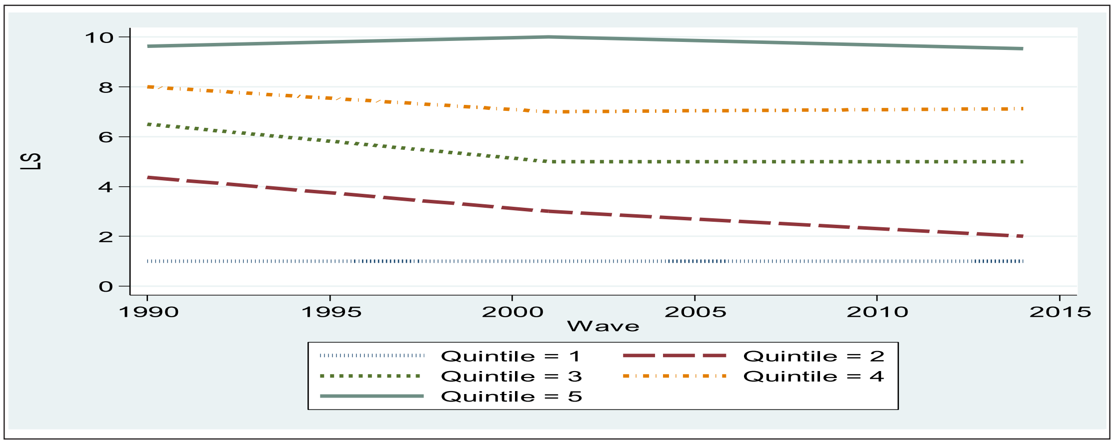


Fig. 7: Life Satisfaction by Income Quintiles in India

CONCLUSION

In the happiness literature, the often disputed finding is the Easterlin paradox that while there is a direct income-happiness relationship at the individual level and within country, at the aggregate cross-country level, the average happiness is pretty much close despite vast differences in income across countries. Further, there is no direct long-run income-happiness association in any country. Critics of the Easterlin puzzle argue that the analysis of average income-happiness relationship does not reveal much. The OLS or ordered probit estimation of the causal relationship is based on the assumptions of linearity in the income effect and the same average effect holds over the entire range of well-being distribution. But, the response of well-being to income changes is not the same for poor and rich and for less satisfied or unhappy and more satisfied or happy people. To identify and estimate the heterogeneity in the income effects across the well-being distribution, this paper replicates the cross-country analysis of happiness studies with cross-states analysis in India. The differential effects of income on the income-life satisfaction relationship at specific locations of the well-being distribution is estimated by the panel quantile regression method.

The descriptive analysis of well-being distribution across states shows heterogeneity in the income-subjective well-being relationship between states and among people within states. The estimated across-states over-time panel quantile regression effects reveal that the estimation of average effect only provides an incomplete picture of the effect of income at both ends of the conditional distribution of well-being indicators, life satisfaction and happiness levels. The quantile estimates vastly differ not only from the mean estimates, but also across the quantiles. The quantile estimates of this paper show a negative effect of average income growth on life satisfaction at all levels of well-being distribution and such impact decreases across quantiles. But, for the income-happiness association, the income effect at both the individual and aggregate levels is mixed and not uniform across quantiles as that of life satisfaction distribution.

Overall, life satisfaction falls and happiness rises with an increase in NSDP per capita and the income effect is strong at the lower end than at the upper end of subjective well-being distribution. The well-being levels decline with an increase in average income more for the poor people, whereas a rise in average income leaves the well-being of higher-income people unaffected. The most-happy people among the rich have only slightly higher happiness level than the most-happy individuals among the poor. An increase in average income at higher income levels increases unhappiness in India and higher income is not necessarily associated with higher subjective well-being. Thus, the income effect on subjective well-being is not the same for all and at income levels in India. In essence, an increase in income is associated strongly with the well-being levels among the unhappy and poor people and weakly with the happy and rich people in the states of India.

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