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Accounting for Longevity: Cross-State Economic Performance in India, 1981-2019

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Abstract

We analyze growth in full income, accounting for the value of reductions in mortality risks, across 15 major Indian states from 1981 to 2019. We followed Becker et al.'s (2005) approach that used the compensating variation method to measure the monetary value of longevity gains. Full income per person in India grew at an annual average rate of 5.8% compared to 4.4% for real income per capita from 1981 to 2019. Longevity gains accounted for 45.5% of full income gains nationally and were higher in poorer states (52%) than in their richer counterparts. There was some evidence of inter-regional divergence, with full income growth in the poorest region averaging 5.3% annually during 1981-2019, compared to 6.4% annually for the richest region over the same period. We also sought to examine economic gains from a gender lens by comparing inter-regional performance in full income based on valuing gains in females' longevity, concluding that gender-inclusive full income grew faster nationally than a measure that did not directly account for it.

Keywords: Economic growth, Longevity, Convergence, Full income, Welfare

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Introduction

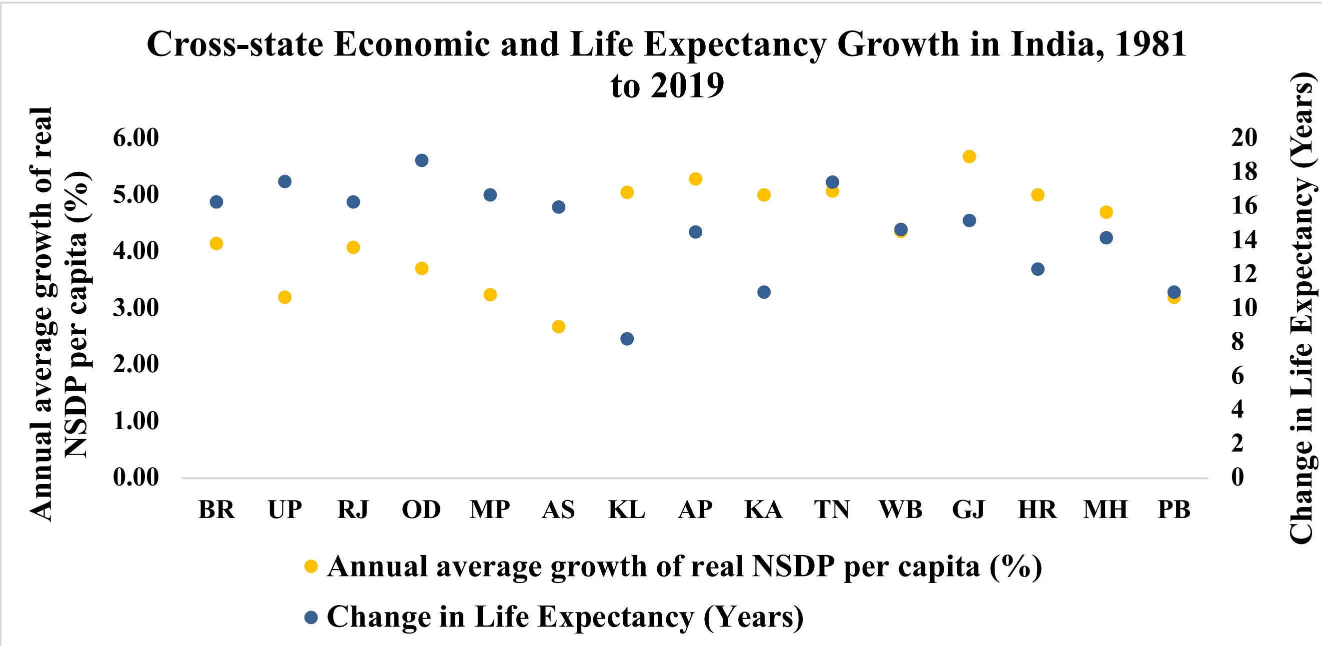
The concept of a full income measure accounting for health improvements has gained prominence in recent literature, as highlighted for instance in Jamison et al.'s (2013) influential report that discusses the importance of incorporating the value of additional life years (VLYs) in national income accounts. This approach contributes firstly, to a fuller understanding of the returns on health investments (Jamison et al., 2013; Murphy & Topel, 2006). Including the value of longevity is critical as Jamison et al. (2013) argue—because individuals intrinsically value a longer and healthier life, as demonstrated, for instance, by their demand for safe living conditions. They stress that the objective is not to assign a monetary value of an individual's life, but to value mortality risk reduction, and thus incorporate it into a full income measure. Full income measures also draw attention to the value of accounting for choices that societies might make in terms of welfare-enhancing investments, such as investments that focus primarily on income growth as against investments that prioritize human capital (such as population health). This perspective is well appreciated for instance in Amartya Sen's capability framework where improved health is viewed as being of intrinsic importance, and not merely as an instrument for achieving improved economic outcomes (Sen, 1985).

Second, at the macroeconomic level, the full income measure helps shed light improvements in wellbeing or living standards not captured in traditional national income measures. Usher (1973) highlighted the importance of accounting for longevity gains when assessing cross-region or cross-country performance. He posited that people in high income countries or regions—as measured by traditional metrics like Gross Domestic Product (GDP) and Gross National Product (GNP)—are assumed to be better off than people in low income countries (Usher, 1973). However, countries might demonstrate different growth patterns depending on the measures of wellbeing used (e.g. the value of longevity gains), underlining the need for more comprehensive national income statistics to assess cross-regional performance. In this context, Becker, Philipson, and Soares (2005) studied cross-country economic performance using a full income measure that incorporated longevity gains in 49 countries from 1965 to 1995. They found that the monetary value of gains in longevity accounted for as much as 28% of the full income growth in the United States with its share ranging from 30% to 85% for low- and middle-income countries such as Venezuela, El Salvador, Egypt, and Chile. The authors also found absolute convergence in cross-country economic outcomes measured by full income (i.e. when including longevity gains). In contrast, if cross-country comparisons were confined to growth in real GDP per capita, there is no evidence of (absolute) convergence, only of *conditional* convergence. The notion of 'absolute convergence' refers to the conclusion, derived from the Solow growth model, that countries with a low initial level of income per capita experience higher rates of economic growth going forward (Barro & Sala-i-Martin, 1992), whereas conditional convergence refers to the empirical finding that convergence holds only after additional contextual variables (e.g. human capital stock) are accounted for (Mankiw et al., 1992).

With this as a background, we study the growth of 'full income', incorporating longevity gains, across 15 Indian states over four decades from 1981 to 2019, rather than relying on growth of GDP per capita alone, which were characterized by major economic and health sector reforms. Specifically, we examined three questions that have attracted attention in the international literature: (a) What is the share of the value of longevity gains (mortality reduction) in full income gains in India? (b) How does accounting for gains in longevity affect our understanding of the relative economic performance of Indian states and regions? (c) Does accounting for gains in women's longevity affect our conclusions about changes in full income and cross-region economic performance?

We are not aware of any previous analysis that captures the growth of full income at the national and state levels in India. During the period from 1981 to 2019, India's real GDP per capita grew at an average annual rate of approximately 4.2% (World Bank, 2024). Individual states have grown at dissimilar rates, with most studies suggesting the existence of conditional convergence (Cherodian & Thirlwall, 2015; Mallick, 2014; Nayyar, 2008; Raj et al., 2024), but not absolute convergence. However, data from Indian states (ranked by income per capita in 1981) shows that their post-1981 growth experience of real income per capita and post-1981 changes in life expectancy at birth varies considerably across states (see Figure 1). The Spearman rank correlation coefficient between the two indicators is -0.322, suggesting a negative association between states' ranking in Net State Domestic Product (NSDP) per capita growth and their ranking in life expectancy improvements.

Figure 1. Change in Real Income per Capita and Life Expectancy at Birth across 15 Major Indian States, 1981-2019



Note: NSDP = Net State Domestic Product. Expanded full forms of state abbreviations are provided in the footnote.[1]
Source: Figures incorporated from the Office of Registrar General & Census Commissioner, India, 2022; Reserve Bank of India, 2024; Sample Registration System (SRS)

Separately, some articles have examined changes in indicators of 'human development' over time across states in India. For example, Ghosh (2006) considered changes in the Human Development Index (a composite measure of three dimensions; life expectancy, education, and income) across 15 Indian states between 1981 and 2001 and concluded that poorer states were catching up with richer states over time. In contrast, Raj et al., 2024 did not find either cross-state

[1] State abbreviations: BR = Bihar; UP = Uttar Pradesh; RJ = Rajasthan; OD = Odisha; MP = Madhya Pradesh; AS = Assam; KL = Kerala; AP = Andhra Pradesh; KA = Karnataka; TN = Tamil Nadu; WB = West Bengal; GJ = Gujarat; HR = Haryana; MH = Maharashtra; PB = Punjab

convergence (or divergence) of the Human Development Index (HDI) for the period after 1990. The HDI however, has received criticism for its conceptual basis, especially in how the various components are weighted in terms of their contribution to human development, and moreover cannot be directly translated into monetary terms (Ravallion, 2012; Srinivasan, 1994; Wolff et al., 2011). In contrast, the approach proposed by Becker, Philipson, and Soares (2005) is based on a compensating variation method, better grounded in economic theory (lifetime utility-based framework), and is practically useful in that it provides a monetary value of longevity gains based on the individuals' willingness to trade income for longevity. With this by way of background, the question arises: is economic progress, as captured by a full income measure that includes the value of longevity gains converging across states in the manner suggested by Becker et al. (2005) in their cross-country study?

We are also unaware of research that specifically accounts for gains in longevity among women that could help shed light on whether economic welfare gains have been gender-inclusive, and whether such gains might be varying across states/regions. Understanding these regional gender disparities, if any, can also help build a case for enhanced investments in female wellbeing, including labor force participation (LFP)—particularly since LFP has been declining in the recent (pre-COVID) years (Andres et al., 2017; Costagliola, 2021; Desai & Joshi, 2019; Dubey et al., 2017). If longevity gains for women are higher but do not translate into greater economic inclusion in some regions it would strengthen the argument for complementary investments in other areas of human development.

The potential significance of a gender-inclusive measure is underlined by a large body of work in India that highlights gender-linked inequalities in economic and social outcomes. For instance, Sen (2001) noted how mortality inequality in India is often driven by neglect of healthcare and nutrition for women and girls, alongside other forms of underinvestment in their human capital. Maternal mortality rates (MMR) in India, estimated at around 400 per 100,000 live births in 1997-1998, have declined to around 99 per 100,000 live births in India in 2020, but continue to be much higher than rates typically observed in upper-middle-income and high-income countries (Meh et al., 2022). Given the well-documented link between income growth (per capita and national level) and health outcomes (Bloom & Canning, 2000)—and the pivotal role gender plays in mediating this relationship (Limacher et al., 2023; MacIntyre & Hunt, 1997)—exploring gender disparities in longevity gains can provide further understanding on whether changes in economic well-being in India have been gender-inclusive.

Our analysis tracks cross-state performance in full income during 1981-2019, which encompasses a period of major economic and health sector reforms and development and thus this research stands to shed light on whether these reform efforts were associated with full income growth. Examples of major reforms that occurred during this period include the economic liberalization that began with the government of Rajiv Gandhi in the mid-1980s, and subsequently, following the fiscal crisis of the early 1990s (Ahluwalia, 2002; Kohli, 2006). In the health sector, a new health policy was launched in 1985, accompanied by investments in maternal and child health. While there was a period of contraction in health spending (as a share of GDP) following the fiscal crisis, steady increases in public sector investments , including the National Health Mission to strengthen primary care began in the early 2000s, including the introduction of publicly funded health insurance at the state and national levels (Ahluwalia, 2002; National Rural Health Mission, 2005; Niti Aayog, 2019, 2021; Panagariya, 2010). Assessing the contribution of longevity gains (monetary terms) after 2001, a period that overlaps with the major health sector investments that were initiated post-2005 can help shed light on whether these reforms were associated with economic welfare gains, and how these gains were distributed regionally.

Data and Methods

Data on Net Domestic Product per Capita (NSDP) for 15 major undivided states (the full list of states included in the study is provided in Appendix Table 3), that account for 93% of India's national income and 91% of its population, was obtained from the Reserve Bank of India, which maintains a longitudinal database of economic variables at the national and state-levels in India. Information on our health-related variables of interest (life tables for each state, aggregated and disaggregated by gender) was not as readily accessible. Instead, life tables were derived by the authors from data on age-specific mortality rates (ASMR) for which information was available (by state and sex) from the Sample Registration System (SRS) reports of the Registrar General and Census Commissioner of India (Office of Registrar General & Census Commissioner, India, 2009, 2022).

Full income was calculated as the sum of NSDP per capita and the monetary value of reductions in mortality risk. Following Becker et al. (2005), the monetary value of a given improvement in the likelihood of survival was assessed using a compensating variation method, i.e. identifying the extra income needed to exactly compensate for foregoing survival gains, all else the same. As in Becker et al., an intertemporal utility function was defined as:

$$V(S, Y) = \int e^{-rt} u(y(t)) S(t) dt \qquad (1)$$

Where $y(t)$ is the income stream, $u(y(t))$ is an instantaneous utility function, $S(t)$ is the survival function, and e^{-rt} denotes discounting. The monetary value of interest is the extra average income (per period or 'per year') needed at a time $t + \Delta t$ to leave a person at the same level of well-being (lifetime expected utility) in $t + \Delta t$, with the survival function given by $S(t)$ instead of $S(t + \Delta t)$.

In any given year, the future income stream is assumed to equal (real) NSDP per capita for that year. Then for a utility function $u\big(y(t)\big)$ of the form given in (2), the extra income required per year to compensate for a survival function $S(t)$ instead of $S(t + \Delta t)$ is given by the formula in (3) (Becker et al 2005).

$$u(y) = \frac{y^{1-\frac{1}{\delta}}}{1-\frac{1}{\delta}} + \alpha \tag{2}$$

$$E \; = \; [y_{t+\Delta t}^{1-\frac{1}{\delta}} \frac{A(t+\Delta t)}{A(t)} + \alpha(1 - \frac{1}{\delta})(\frac{A(t+\Delta t)-A(t)}{A(t)})]^{\frac{\delta}{\delta-1}} - y_{t+\Delta t} \tag{3}$$

Where $A(t) \equiv \int e^{-rt}\, S(t) dt$, α the parameter captures the level of consumption equivalent to death and δ is the intertemporal elasticity of substitution. For our calculations we assumed the same values of utility function parameters as Becker et al (2005)[2], and the maximum age to which individuals live is assumed to be 100.[3] Crucially, we needed survival functions for each year for which we needed to assess the value of gains in longevity, with the base year (1981) as the reference year. For our analysis and based on the availability of data, full income measures were constructed for 4 years, roughly about a decade apart: 1991, 2001, 2011, and 2019.

Accounting for Gender

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[2] Becker et al. 2005 used δ = 1.25 to generate a value of α = –14.97. A discount rate of 3% (r = 0.03) was used in their paper. We used these same values in this study.

[3] The average life expectancy at birth in India is 68.6 years for males and 71.4 years for females based on the latest SRS report. The highest average life expectancy was recorded by the state of Kerala at 75 years (overall) and 78 years (females).

We assumed that NSDP per capita was the same for men and women to compute the gender-adjusted full income measure. We acknowledge the need for a gender-adjusted economic measure like the GDP per capita, as also underscored in the development economics literature and by feminist scholars (Benería, 1992; DeRock, 2021; Waring, 2003). One way to resolve this would be to look at the consumption spending per capita for women, as it is likely to better reflect the well-being of individuals, as income might not adequately capture intra-household resource allocation (Deaton, 1989; Osberg & Sharpe, 2002; Ringen, 1991). However, obtaining data on consumption separately for women and men is not straightforward. In India, consumer expenditure data is collected at the household level in existing surveys, making it difficult to disaggregate by gender. Previous attempts to compare the consumption per capita of female-headed and male-headed households across sectors such as health and education (Pradhan, 2022) have not provided much insight into individual-level consumption differences between women and men within households.

Other efforts have been made at computing gender-specific consumption shares by applying welfare weights on male and female income earners (Bourguignon et al., 1993; Browning et al., 1994; Lancaster et al., 2008). However, this approach estimates budget shares influenced by the gender of 'income earners' and bargaining power, ignoring the unpaid work by women or their indirect contributions to the economy, such as caregiving for adults and children, voluntary work, and household tasks (which are typically not recognized as formal employment). The value of unpaid household tasks (excluding subsistence production of goods) or unpaid domestic work such as caregiving, which is not included in the System of National Accounts (SNA) is unaccounted for in NSDP per capita (Gaddis & Klasen, 2014; Hirway, 2015; United Nations Development Programme, 1995). Furthermore, the definition of 'employment' and what constitutes ‘unemployment’ is of relevance here. Para 1.22 of the sub-section ‘Production Boundary’ of the Introduction of the 1993 United Nations SNA (also updated in the 2008 version) states the concept of employment as - “If the production boundary were extended to include the production of personal and domestic services by members of households for their own final consumption, all persons engaged in such activities would become self-employed, making unemployment virtually impossible by definition.” (United Nations et al., 1993). As highlighted by Waring (2003), this conceptualization underscores the recognition of women’s efforts regardless of their formal employment status, rather than excluding household work and their caregiving efforts. Data on unpaid work exists in time use surveys however, adding the income equivalent of domestic work for females to the average NSDP per capita might inflate the income figure (despite accounting for men’s unpaid work since women’s contribution is reportedly much higher i.e.16.4% for unpaid domestic work compared to 1.70% in the latest 2024 Indian time use survey). Unfortunately, data from the time-use surveys exist for 2019 and 2024 only, while the analysis in our context spans from 1981 to 2019. To address these concerns, we assumed income per capita to be the same for both men and women. We recognize that female LFP has been declining in India (Andres et al., 2017; Costagliola, 2021; Desai & Joshi, 2019; Dubey et al., 2017) however, our model does not account for this decline directly. By assuming uniform income per capita, we are (by extension) equating domestic and unpaid labor to paid work, thus deliberately abstracting from the composition of labor force.

Computation of Survival Functions

To construct population and gender-disaggregated survival functions for 1981, 1991, 2001, 2011, and 2019, we first derived life tables using data on age-specific death rates (ASDR) for each of these years. Because the period 1981-2019 also included the time when Madhya Pradesh, Uttar

Pradesh, and Bihar were sub-divided into smaller states, we constructed survival functions for the undivided (pre-2001) states for 2011 and 2019. Similarly, Telangana separated from Andhra Pradesh (AP) in 2014, so we generated a lifetable for undivided AP for the year 2019. Population weights were used to generate composite life tables (and survival functions) for the undivided states. We restricted our analysis to the period from 1981 to 2019 to exclude the effects of the COVID-19 pandemic on mortality, and thus on full income measures.

Construction of information on the probability of survival for each year from the time of birth (i.e. the survival function) for 1981, 1991, 2001, 2011, and 2019, required the conversion of data on age-specific death rates (ASDR) into life tables. Publicly accessible ASDR data for India are only provided for age intervals (i.e. abridged) instead of individual years (unabridged). Thus, the first step was to construct unabridged life tables from ASDR data. Because there are multiple methods of undertaking this 'conversion', our choice was determined by how well the estimates of life expectancy at birth based on these life tables approximated (official) life expectancy numbers published in the SRS reports for the corresponding years. Four different methods were considered for this purpose: the Gompertz model, Constant Exponential Growth, Linear Extrapolation, and Three-year Moving Average (APHEO, 2024; Chatfield, 2016; Gompertz, 1997; Lee & Carter, 1992; Additional details are provided in the Appendix).

The Gompertz model yielded life expectancy estimates that were closest to SRS reports, hence, we mostly used this model for the exercise of constructing life tables from ASDR, except for Assam and in a few other instances where it did not perform well in terms of capturing the official estimates of life expectancy at birth (we used the three-point moving average method for these other cases). These state-specific adjustments were made to obtain survival functions that were close to the official measure of life expectancy. We have detailed all the methods in the

Appendix. The Gompertz Model is based on the Gompertz Law of Human Mortality first described in 1825 by Benjamin Gompertz. The law suggests that the risk of dying (mortality rate) increases exponentially as the age of an individual increases (Gompertz, 1997). It is given by $m_x = Ae^{bx}$, where m_x is the age-specific mortality rate, or in this case, the age-specific mortality rate at age 'x'. 'A' is the baseline mortality rate and 'b' is the rate at which the mortality increases. The baseline mortality rate is the initial mortality rate before exponentiation occurs. The formula used for the computation was $ln(m_x) = a + bx$ (details provided in Technical Appendix).

Testing for Convergence

While examining the cross-state performance in the longevity gains can help provide insights into the relative significance of longevity in full-income it also allows an assessment of whether poorer states were catching up with (or diverging from) the richer states in terms of the longevity-adjusted full income measure. We ranked 15 major Indian states into 4 (regional) categories based on their NSDP per capita income in 1981 (Table 2 in the Appendix) and checked for existence of absolute (or 'beta') convergence at the state level by regressing the growth of NSDP per capita and the full income measures (including the gender-inclusive counterpart of full income) during 1981-2019 on the natural log of the NSDP per capita in 1981 for 15 states. For the full period (1981–2019), the dependent variables were the annual average growth rates of real NSDP per capita and the comprehensive income measure, with the natural logarithm of real NSDP per capita in the base year (1981) serving as the explanatory variable. Similarly, for the sub-period 2001–2019, the natural logarithms of full income per capita and NSDP per capita in the base year (2001) were used as explanatory variables.

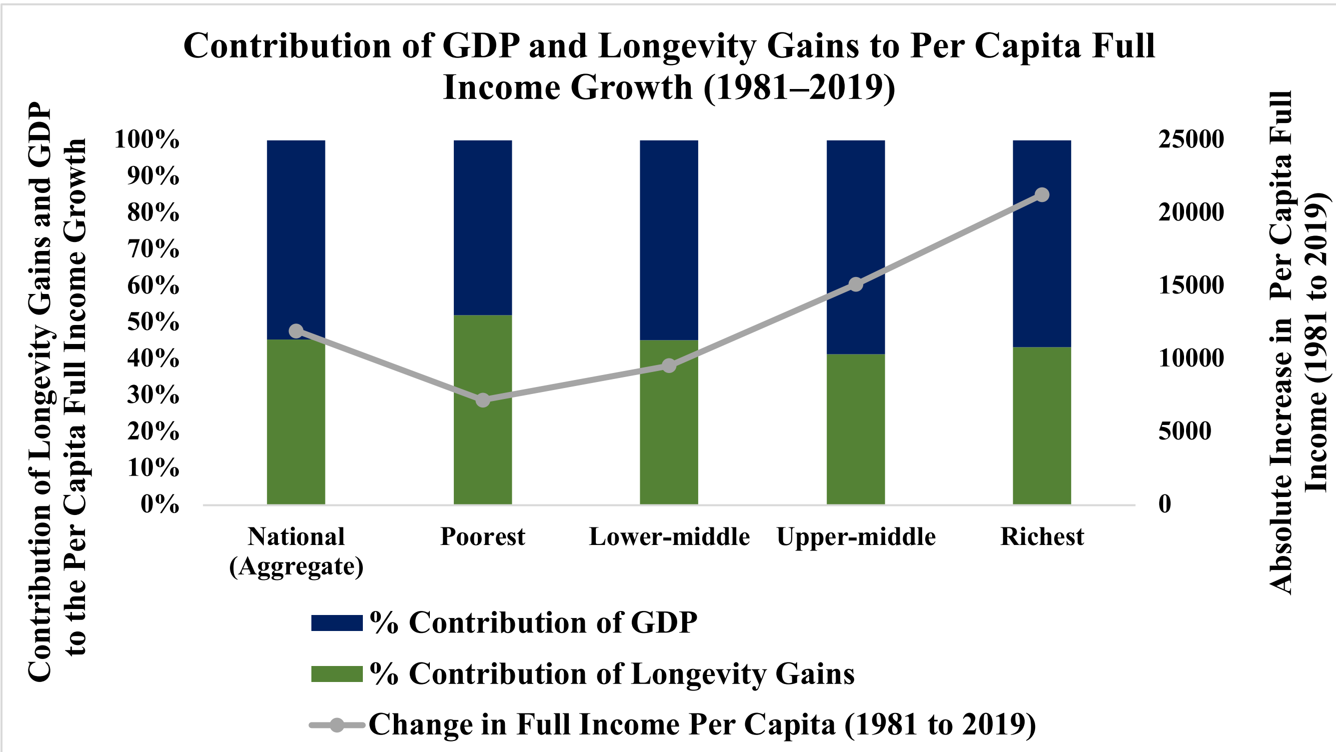
We also assessed the dispersion (or spread) of per capita income and full income across the 15 states during 1981 to 2019. A reduction in dispersion is sometimes referred to as 'sigma convergence’ in the literature (Sala-i-Martin, 1996). For this purpose, we calculated the Coefficient of Variation (ratio of standard deviation to the mean) of real income per capita and its full income counterpart across states from 1981 to 2019.

Results

Share of Longevity Gains

Figure 2 describes our findings on the absolute change in full income from 1981 to 2019, and the relative contribution of longevity and NSDP per capita to the change in full income, nationally and for regions ranked by NSDP per capita in 1981. While full income experienced a larger change in absolute value in the richer regions, the contribution of longevity gains to full income was greatest in the poorest group of states (52.0%). In comparison, the share of longevity in full income gains was 41.0% in the upper-middle income states and 43.3% in the states comprising the richest group. Nationally, the contribution of longevity to gains in full income was 45.5%. Results on full income growth and the contribution of longevity gains for individual states are reported in the Appendix (Figure 9). Madhya Pradesh (MP), Uttar Pradesh (UP), and Rajasthan (RJ) had the highest share of longevity in their gains in full income: 58.1%, 55.1%, and 52.5% respectively. Among the high-income states, Gujarat (GJ) had the highest contribution of longevity gains of 49%. Kerala (KL) had the lowest contribution of longevity gains to growth in full income (19.4%), likely reflecting its high baseline life expectancy.

Figure 2. Contribution of Longevity Gains and Income per Capita to Full Income Gains across States, 1981-2019



Note: The regions presented in the figure are "economic" regions, comprising states classified based on the Net State Domestic Product (NSDP) per capita in constant prices in 1981 with 1980-81 as the base year.[4]
Source: Authors' estimates

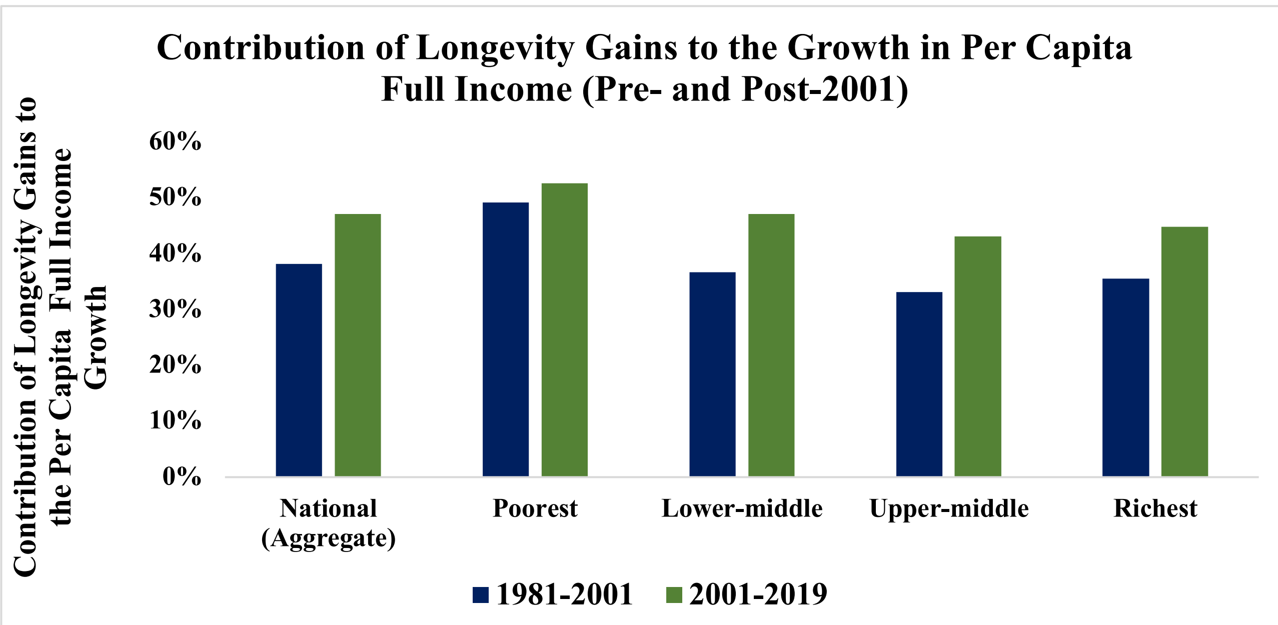
Contribution of Longevity Contribution to Change in Full Income: 1981-2001 versus 2001-2019

Figure 3 reports the contribution of longevity gains to the full income growth segregated by different sub-periods—1981 to 2001, and 2001 to 2019. While the contribution of longevity gains to the full income growth was larger across regions in the period after 2001, the poorest

[4] Poorest = Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD); Lower-middle = Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP); Upper-middle = Karnataka (KA), Tamil Nadu (TN), West Bengal (WB); Richest = Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)

regions had the highest contribution from longevity gains in both periods. Before 2001, the contribution was notably higher in the poorest regions (49%) compared to the richest (35%). This disparity narrowed post-2001; longevity gains accounted for 53% of full income growth in the poorest regions versus 43% in the richest.[5] Detailed results at the state level are available in the Appendix (Figure 10).

Figure 3. Inter-region performance of longevity gains pre- and post-2001



[5] For the post-2001 period, we calculated the values by subtracting the population-weighted per capita full income growth (and the monetary value of longevity gains) for 1981–2001 from the corresponding figures for 1981–2019.

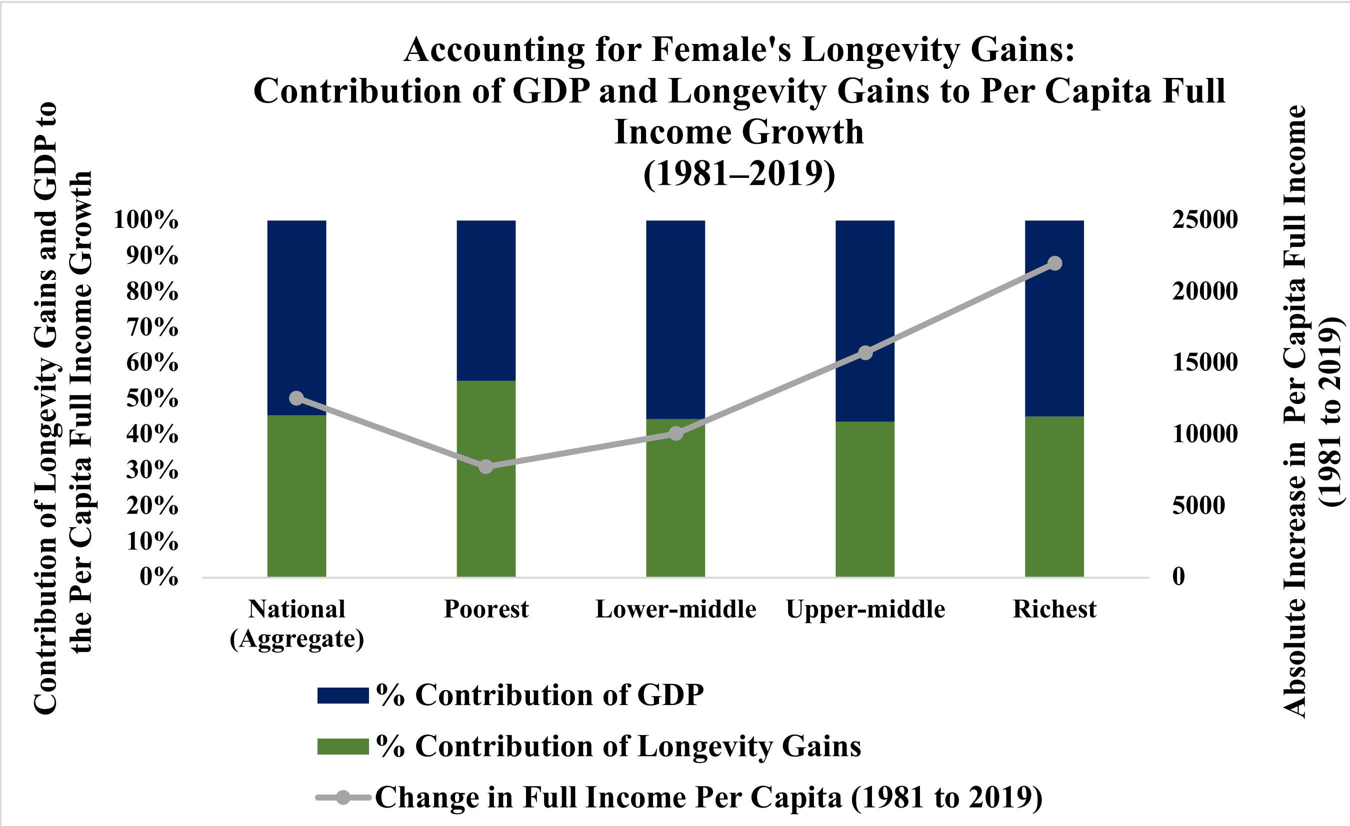
Note: The regions presented in the figure are "economic" regions, comprising states classified based on the Net State Domestic Product (NSDP) per capita in constant prices in 1981 with 1980-81 as the base year.[6]
Source: Authors' estimates

Accounting for gains in women's longevity

Figure 4 describes changes in a gender-adjusted full income measure from 1981 to 2019, that accounts for gains in women's longevity. Including the value of longevity gains among women in full income yields the familiar pattern of the richest states/regions experiencing the highest absolute change in full income, and the poorest states accounting for the largest share of longevity in gains experienced in full income (55.2%). Results for individual states are available in the Appendix (Figure 11).

Figure 4. Contribution of Female Longevity Gains and GDP to Absolute Full Income Growth from 1981 to 2019

[6] Poorest = Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD); Lower-middle = Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP); Upper-middle = Karnataka (KA), Tamil Nadu (TN), West Bengal (WB); Richest = Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)



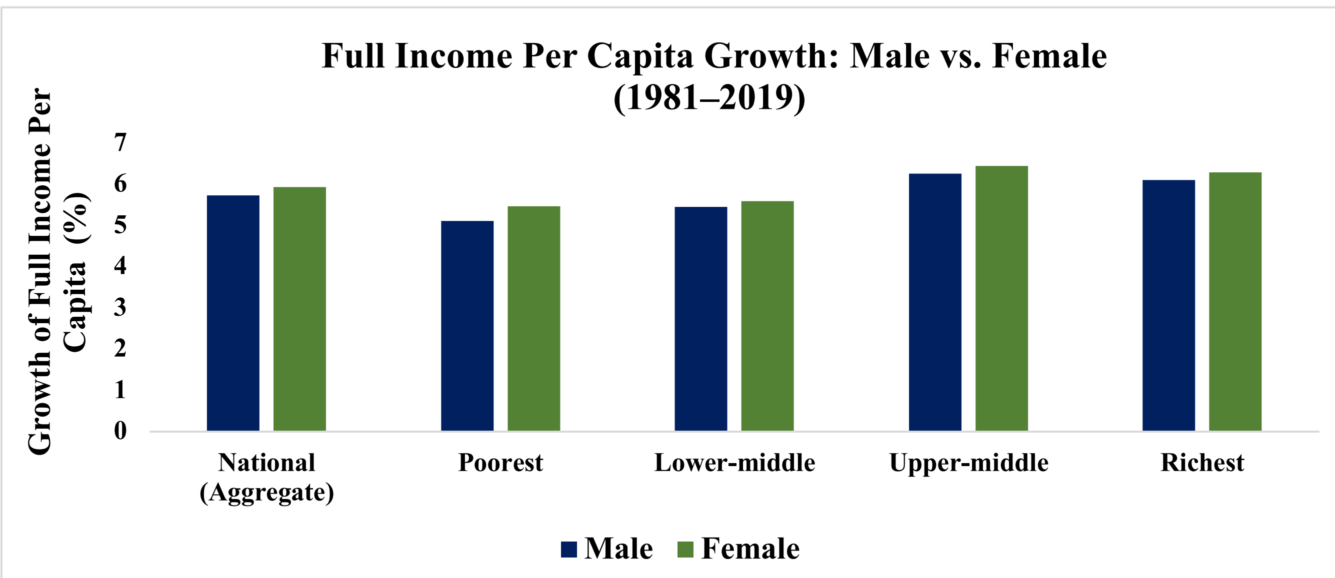
Note: The regions presented in the figure are "economic" regions, comprising states classified based on the Net State Domestic Product (NSDP) per capita in constant prices in 1981 with 1980-81 as the base year.[7]
Source: Authors' estimates

Figure 5 describes the annual average rate of full income growth for two gender-adjusted measures – one that uses gains in longevity only among women, and a second that considers longevity gains only among men. The (slightly) faster growth of full income when accounting for women's longevity gains is indicative of a small decline in gender disparities vis-à-vis life expectancy over time. Nationally, per capita full income gains among women exceeded that of men by 7.4% over the period of study. The difference is particularly pronounced in the poorest

[7] Poorest = Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD); Lower-middle = Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP); Upper-middle = Karnataka (KA), Tamil Nadu (TN), West Bengal (WB); Richest = Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)

and richest regions, where full income gains among women exceed those of men by 11% and 10%, respectively, compared to 3% and 1% in the lower- and upper-middle regions. Haryana had the highest difference, with the monetary gains of mortality risk reduction for females exceeding males by 23%. Similarly, states like Gujarat, Uttar Pradesh, Rajasthan, Madhya Pradesh, and Tamil Nadu also demonstrated substantially higher monetary longevity gains for females compared to males (results for individual states are available in Table 4 of the Appendix).

Figure 5. Per Capita Full Income Growth (Men versus Women), 1981 to 2019



Note: The regions presented in the figure are "economic" regions, comprising states classified based on the Net State Domestic Product (NSDP) per capita in constant prices in 1981 with 1980-81 as the base year.[8]
Source: Authors' estimates

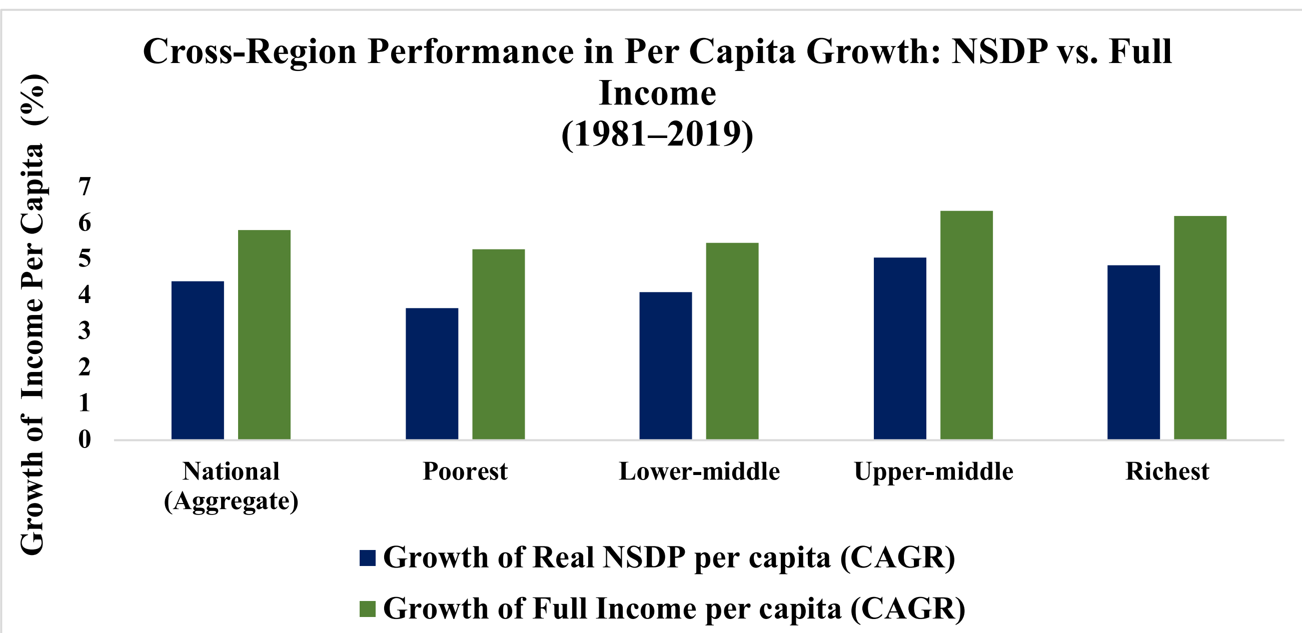
Convergence in Full Income versus Convergence in Real NDSP per Capita

[8] Poorest = Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD); Lower-middle = Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP); Upper-middle = Karnataka (KA), Tamil Nadu (TN), West Bengal (WB); Richest = Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)

Beta (or Absolute) Convergence

Regionally, the annual average growth of full income per person in the poorest group of states was 5.3% – lower than in the upper-middle (6.4%) and richest (6.2%) groups of states, suggesting inter-regional divergence (not convergence) in full income (Figure 6). Figure 12 in the Appendix illustrates the corresponding comparison of inter-state economic performance (NSDP per capita and full income per capita) for the period from 1981 to 2019 and shows that the performance of Bihar (BR), Uttar Pradesh (UP), Rajasthan (RJ), Madhya Pradesh (MP), and Odisha (OD) (which belonged to the poorest group of states in 1981 in terms of NSDP per capita) lagged the richer states in the growth of full income during 1981-2019.

Figure 6. Full income and real NSDP per capita growth by region, 1981 to 2019



Note: NSDP = Net State Domestic Product; CAGR = Compound Annual Growth Rate. The regions presented in the figure are "economic" regions, comprising states classified based on the Net State Domestic Product (NSDP) per capita in constant prices in 1981 with 1980-81 as the base year.[9]
Source: Authors' estimates

The preceding results suggest that contrary to Becker et al. (2005), poorer states in India are not catching up with their richer counterparts, whether in terms of NDSP per capita, or full income per capita (i.e. no beta convergence). Table 1 reports regression results that further underline this finding, including for specific sub-periods: 1981-2019, 1981-2001, and 2001-2019. The positive coefficients of the base year NSDP suggest that full income did not absolutely converge across states in India in any of the three periods. The evidence for divergence is also weak, however, given the large standard errors.

Table 1. Testing for Beta (or Absolute) Convergence of Full Income and Real NSDP per Capita in India, 1981-2019

Period	Constant	Coefficient on the log of initial income per capita	R^2
Panel A: Full Income Growth			
1981-2019	-0.002 (0.056)	0.006 (0.007)	0.054
1981-2001	-0.038 (0.069)	0.010 (0.009)	0.089
2001-2019	0.039 (0.071)	0.002 (0.009)	0.003
Panel B: Real NSDP per capita Growth			

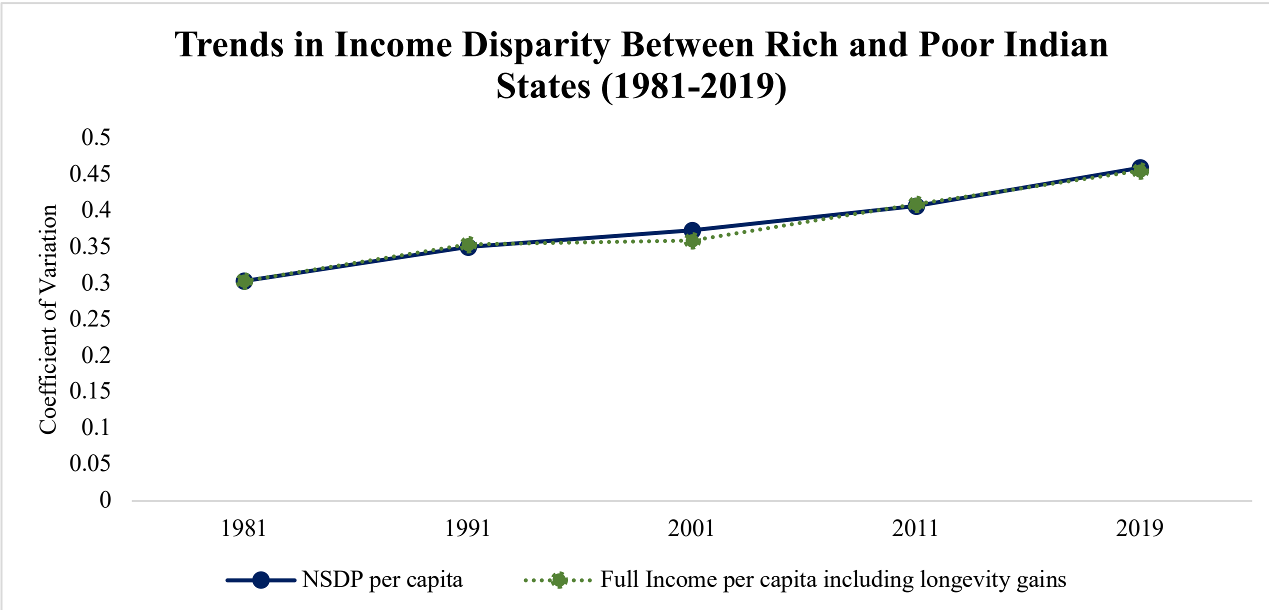
[9] Poorest = Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD); Lower-middle = Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP); Upper-middle = Karnataka (KA), Tamil Nadu (TN), West Bengal (WB); Richest = Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)

1981-2019	-0.015 (0.058)	0.007 (0.008)	0.067
1981-2001	-0.069 (0.060)	0.013 (0.008)	0.169
2001-2019	0.011 (0.062)	0.006 (0.007)	0.041

Notes: (a) Standard errors in parentheses
(b) N = 15 (states)

Figure 7 plots the coefficient of variation (CV) for both NSDP per capita and full income per capita (including longevity gains) over time for the 15 states included in this paper. As demonstrated in both graphs, the CV (our indicator of sigma-convergence) increased steadily from 1981 to 2019, indicating growing inequality across states. The results for gender-inclusive full income are similar (Figure 13 in Appendix).

Figure 7. The dispersion of full income per capita across Indian states, 1981 to 2019



Source: Authors' estimates

Discussion

Previous research has emphasized the need to account for full income measures to better capture the value of gains to health instead of relying on traditional national income measures. Our paper does this for the first time for India, while accounting for sub-national variation in major states. Full income in India grew considerably faster (annual average growth rate of 5.8%) than real NSDP per capita which grew at an annual average of 4.4% during the period 1981 to 2019. Longevity gains accounted for 45.5% of the gains in full income during this period. Moreover, the value of improvements in survival accounted for a larger share of the full income gains observed in poorer states than for their richer counterparts. These results align with the findings of Becker, Philipson, and Soares' (2005), who conclude that poorer countries demonstrated higher contribution of longevity gains to full income growth. Introducing a gender-inclusive full income measure did not change these results significantly but is suggestive of improvements in gender equity. We did not find any evidence of convergence in full income across Indian states during 1981-2019, an extension of previous findings for India which did not find convergence in real NSDP per capita across states (Ghosh, 2008). There is some weak evidence in favour of absolute divergence, however. Our findings are not consistent with Becker, Philipson, and Soares' (2005) conclusion of absolute cross-country convergence in full income.

Prima facie, the findings on relatively faster growth of full income in the poorer states and their larger share of longevity in gains in full income are broadly consistent with expected outcomes under a government strategy of prioritizing investments in primary care, especially maternal and child health conditions, in poorer states in India. While public health spending in India has remained relatively low as a share of GDP, ranging between 0.8%-1.2% over the last 2 decades, initiatives such as the National Rural Health Mission (NRHM), launched in 2005, have sought to enhance public spending on primary care, especially in poorer states (National Rural Health Mission, 2005; World Bank, 2024). One potential explanation for the higher contribution of longevity gains in full income for the poorest states is that improvements in health are likely to be greater in absolute terms for the same level of investment if one is starting from low baseline levels of health. Figure 11 in the Appendix supports this reasoning; states like Odisha (OD), Bihar (BR), Uttar Pradesh (UP), Madhya Pradesh (MP), and Assam (AS) exhibited higher longevity gains ranging from 40%-58%. They had lower life expectancies in 1981 (all below 53 years) in comparison to other states (which also happened to be their richer counterparts). In contrast, Kerala and Karnataka, with relatively higher life expectancies at the start (and higher NSDP per capita), saw the lowest contributions of longevity gains (ranging from 18%-20%) between 1981 and 2019.

Theoretically, the higher monetary values of longevity gains (1981 to 2019) of the poorer states like MP (58%), UP (55%) and Rajasthan (52%) would be plausible. Higher monetary values would in this context imply that higher incomes are required to compensate for survival gains (or to accept the gain), thus suggesting that poorer individuals may value longevity gains less than their richer counterparts in utility-equivalent terms.[10] This pattern aligns with the intuition from Becker et al.'s (2005) framework, where the monetary compensation for survival gains depends on both the intertemporal elasticity of substitution (IES) and the magnitude of longevity improvement. Individuals with lower IES values are less willing to trade off their current consumption for future survival gains.[11] Our analysis considers the uniform IES of 1.25 across regions (poor and rich), as in Becker et al.'s (2005) paper. However, the poor might display a lower IES than the rich. In a paper that used data from household panel survey for India from1974 to 1981, Atkeson & Ogaki (1996) found economically significant differences in the IES between the poorest (0.5) and the richest households (0.8) (Atkeson & Ogaki, 1996). To test this heterogeneity, we substituted these values into Becker et al.'s (2005) framework, and observed how the monetary values of the poorest states changed in comparison to their richer counterparts with higher IES (Table 6 in Appendix). Interestingly, the monetary value of longevity gains decreased in the poorest states. This perhaps suggests that a lower IES might lead to the poorest regions (or individuals) being more accepting of the income equivalent of a survival gain, as opposed to their richer counterparts with higher IES that need higher compensations to adjust their lifetime consumption in response to longevity gains. More recent data for India suggests a much higher income elasticity of substitution of 2.2 (Kapoor & Ravi, 2017), but the estimates are not separately available for different income levels. Substituting the IES value of 2.2 in the framework led to

[10] The 'value' referenced here pertains to utility-compensation terms and not normative claims about which regions value longevity more or less

[11] Analyses vis-à-vis IES depends on population distribution. However, in the absence of such detailed data, the reasoning is provided based on aggregated state- and region-level data.

higher monetary values for all states, with the increase being especially marked in the poorest states (Table 6 in Appendix), thus aligning with our study's overall finding.

Our study also finds higher monetary values of longevity gains for females versus males, mainly because longevity gains among women are higher. Even this may underestimate the true value of longevity gains to women since estimates available in the literature report IES for women than for men (Yagihashi & Du, 2023), implying that they would require higher income compensation to forgo gains in survival. Thus, if the appropriate gender-specific IES values were incorporated into Becker et al.'s (2005) framework, this could also result in larger monetary values of longevity gains for females than males.

This also brings us to the question of what impact (if any) policy interventions like the National Rural Health Mission (NRHM) launched in 2005 — analogous to equity or merit goods subsidy — may have had on the monetary values of longevity gains post-2001. One mechanism through which NRHM might have an effect is via longevity gains, and thus the value of the contribution of longevity gains. However, interventions such as NRHM (primarily targeted towards the poor), can alter individuals' behavior by subsidizing healthcare, thus freeing up resources that were otherwise would be used for immediate consumption—thus making intertemporal substitution more attractive for individuals (that is, raise IES). Based on our previous argument, this would perhaps lead to higher income compensations post-2001. We had a similar finding where the imply that perhaps we are underestimating the contribution of longevity gains to full income growth post-2001 in poorer states. Public health spending can also be envisioned as a subsidy that influences behavior.

Public investments in health are only one piece of the puzzle, however. Overall, rising household incomes are likely to have played a major role, especially since improvements in nutrition, housing, and sanitation that typically accompany improved economic status play a major role in improved health, especially for poorer households with low initial levels of health. Income may also mediate the effect of public spending on health outcomes, although the evidence on this subject is unclear (Bhalotra, 2007).

Conclusion

Our study analyzes the growth in full income, accounting for the value of reductions in mortality risks, across 15 major Indian states from 1981 to 2019. While there was no conclusive evidence of convergence in full income across Indian states during 1981-2019, 1981-2001 and 2001-2019, the contribution of longevity gains was highest for the poorest regions during all three time periods.

Our paper contributes to the literature on formulation of richer monetary measures of economic progress than GDP and NSDP. Nonetheless there are clear limitations to our analysis. For instance, the key utility function parameters used to derive the monetary value of gains to survival are obtained from Becker et al. (2005) and are not specific to India. A better accounting of the value of Indian women's contribution to economically productive work (including unpaid work such as caregiving for other household members or family farms) is also desirable, although this will require greater attention in time use surveys to obtain more detailed measures on individual members contributions to paid and unpaid work. Addressing these gaps in future research will not only help generate more accurate measures of full income measures that reflect health gains, but also contribute to the broader discussion on how to account for women's contribution to economic value. With context-specific parameters, further research could shed light on whether poorer regions or female populations are more responsive to longevity gains, and to policy interventions (or investments) aimed at reducing mortality risk in these demographics.

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References

Ahluwalia, M. S. (2002). Economic Reforms in India Since 1991: Has Gradualism Worked? *Journal of Economic Perspectives*, *16*(3), 67–88. https://doi.org/10.1257/089533002760278721

Andres, L. A., Dasgupta, B., Joseph, G., Abraham, V., & Correia, M. (2017). *Precarious Drop: Reassessing Patterns of Female Labor Force Participation in India* (SSRN Scholarly Paper 2948511). Social Science Research Network. https://papers.ssrn.com/abstract=2948511

APHEO. (2024). *APHEO - 10 Methods for Calculating Moving Averages*. https://core.apheo.ca/index.php?pid=186

Atkeson, A., & Ogaki, M. (1996). Wealth-varying intertemporal elasticities of substitution: Evidence from panel and aggregate data. *Journal of Monetary Economics*, *38*(3), 507–534. https://doi.org/10.1016/S0304-3932(96)01290-1

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223–251.

Becker, G. S., Philipson, T. J., & Soares, R. R. (2005). The Quantity and Quality of Life and the Evolution of World Inequality. *American Economic Review*, *95*(1), 277–291. https://doi.org/10.1257/0002828053828563

Benería, L. (1992). Accounting for women's work: The progress of two decades. *World Development*, *20*(11), 1547–1560. https://doi.org/10.1016/0305-750X(92)90013-L

Bhalotra, S. (2007). Spending to save? State health expenditure and infant mortality in India. *Health Economics*, *16*(9), 911–928. https://doi.org/10.1002/hec.1260

Bloom, D. E., & Canning, D. (2000). The Health and Wealth of Nations. *Science*, *287*(5456), 1207–1209. https://doi.org/10.1126/science.287.5456.1207

Bourguignon, F., Browning, M., Chiappori, P.-A., & Lechene, V. (1993). Intra Household Allocation of Consumption: A Model and Some Evidence from French Data. *Annales d'Économie et de Statistique*, *29*, 137–156. https://doi.org/10.2307/20075899

Browning, M., Bourguignon, F., Chiappori, P.-A., & Lechene, V. (1994). Income and Outcomes: A Structural Model of Intrahousehold Allocation. *Journal of Political Economy*, *102*(6), 1067–1096. https://doi.org/10.1086/261964

Chatfield, C. (2016). *The Analysis of Time Series: An Introduction, Sixth Edition*. CRC Press.

Cherodian, R., & Thirlwall, A. P. (2015). Regional disparities in per capita income in India: Convergence or divergence? *Journal of Post Keynesian Economics*, *37*(3), 384–407. https://doi.org/10.1080/01603477.2015.1000109

Costagliola, A. (2021). Labor Participation and Gender Inequalities in India: Traditional Gender Norms in India and the Decline in the Labor Force Participation Rate (LFPR). *The Indian Journal of Labour Economics*, *64*(3), 531–542. https://doi.org/10.1007/s41027-021-00329-7

Deaton, A. (1989). Looking for Boy-Girl Discrimination in Household Expenditure Data. *The World Bank Economic Review*, *3*(1), 1–15. https://doi.org/10.1093/wber/3.1.1

DeRock, D. (2021). Hidden in Plain Sight: Unpaid Household Services and the Politics of GDP Measurement. *New Political Economy*, *26*(1), 20–35. https://doi.org/10.1080/13563467.2019.1680964

Desai, S., & Joshi, O. (2019). The Paradox of Declining Female Work Participation in an Era of Economic Growth. *The Indian Journal of Labour Economics*, *62*(1), 55–71. https://doi.org/10.1007/s41027-019-00162-z

Dubey, A., Olsen, W., & Sen, K. (2017). The Decline in the Labour Force Participation of Rural Women in India: Taking a Long-Run View. *The Indian Journal of Labour Economics*, *60*(4), 589–612. https://doi.org/10.1007/s41027-017-0085-0

Gaddis, I., & Klasen, S. (2014). Economic development, structural change, and women's labor force participation: *Journal of Population Economics*, *27*(3), 639–681. https://doi.org/10.1007/s00148-013-0488-2

Ghosh, M. (2006). Economic Growth and Human Development in Indian States. *Economic and Political Weekly*, *41*(30), 3321–3329.

Ghosh, M. (2008). Economic Reforms, Growth and Regional Divergence in India. *Margin: The Journal of Applied Economic Research*, *2*(3), 265–285. https://doi.org/10.1177/097380100800200303

Gompertz, B. (1997). XXIV. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. In a letter to Francis Baily, Esq. F. R. S. &c. *Philosophical Transactions of the Royal Society of London*, *115*, 513–583. https://doi.org/10.1098/rstl.1825.0026

Hirway, I. (2015). Unpaid work and the economy: Linkages and their implications. *Indian Journal of Labour Economics*, *58*(1), 1–21. https://doi.org/10.1007/s41027-015-0010-3

Jamison, D. T., Summers, L. H., Alleyne, G., Arrow, K. J., Berkley, S., Binagwaho, A., Bustreo, F., Evans, D., Feachem, R. G. A., Frenk, J., Ghosh, G., Goldie, S. J., Guo, Y., Gupta, S., Horton, R., Kruk, M. E., Mahmoud, A., Mohohlo, L. K., Ncube, M., … Yamey, G. (2013). Global health 2035: A world converging within a generation. *The Lancet*, *382*(9908), 1898–1955. https://doi.org/10.1016/S0140-6736(13)62105-4

Kapoor, M., & Ravi, S. (2017). Elasticity of Intertemporal Substitution in Consumption in the Presence of Inertia: Empirical Evidence from a Natural Experiment. *Management Science*, *63*(12), 4188–4200. https://doi.org/10.1287/mnsc.2016.2564

Kohli, A. (2006). Politics of Economic Growth in India, 1980-2005: Part I: The 1980s. *Economic and Political Weekly*, *41*(13), 1251–1259.

Lancaster, G., Maitra, P., & Ray, R. (2008). Household Expenditure Patterns and Gender Bias: Evidence from Selected Indian States. *Oxford Development Studies*, *36*(2), 133–157. https://doi.org/10.1080/13600810802037803

Lee, R. D., & Carter, L. R. (1992). Modeling and Forecasting U. S. Mortality. *Journal of the American Statistical Association*, *87*(419), 659–671. https://doi.org/10.2307/2290201

Limacher, R., Hajjioui, A., Fourtassi, M., & Fekete, C. (2023). Does gender moderate the association between socioeconomic status and health? Results from an observational study in persons with spinal cord injury living in Morocco. *Frontiers in Rehabilitation Sciences*, *4*, 1108214. https://doi.org/10.3389/fresc.2023.1108214

MacIntyre, S., & Hunt, K. (1997). Socio-economic Position, Gender and Health: How Do They Interact? *Journal of Health Psychology*, *2*(3), 315–334. https://doi.org/10.1177/135910539700200304

Mallick, J. (2014). Regional convergence of economic growth during post-reform period in india. *The Singapore Economic Review*, *59*(02), 1450012. https://doi.org/10.1142/S021759081450012X

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A Contribution to the Empirics of Economic Growth*. *The Quarterly Journal of Economics*, *107*(2), 407–437. https://doi.org/10.2307/2118477

Meh, C., Sharma, A., Ram, U., Fadel, S., Correa, N., Snelgrove, J., Shah, P., Begum, R., Shah, M., Hana, T., Fu, S., Raveendran, L., Mishra, B., & Jha, P. (2022). Trends in maternal mortality in India over two decades in nationally representative surveys. *BJOG: An International Journal of Obstetrics & Gynaecology*, *129*(4), 550–561. https://doi.org/10.1111/1471-0528.16888

Murphy, K. M., & Topel, R. H. (2006). The Value of Health and Longevity. *Journal of Political Economy*, *114*(5), 871–904. https://doi.org/10.1086/508033

National Rural Health Mission. (2005). National Rural Health Mission (2005-2012)—Mission document. *Indian Journal of Public Health*, *49*(3), 175–183.

Nayyar, G. (2008). Economic Growth and Regional Inequality in India. *Economic and Political Weekly*, *43*(6), 58–67.

Niti Aayog. (2019). *Health System for a New India: Building Blocks. Potential Pathways to Reform*.

Niti Aayog. (2021). *Investment Opportunities in India's Healthcare Sector*.

Office of Registrar General & Census Commissioner, India. (2009). *Compendium of India's Fertility and Mortality Indicators 1971—2013*. Office of Registrar General & Census Commissioner, India.

Office of Registrar General & Census Commissioner, India. (2022). *SRS Based Abridged Life Tables 2016-20*.

Osberg, L., & Sharpe, A. (2002). An Index of Economic Well–Being for Selected OECD Countries. *Review of Income and Wealth*, *48*(3), 291–316. https://doi.org/10.1111/1475-4991.00056

Panagariya, A. (2010). *India: The Emerging Giant*. Oxford University Press.

Pradhan, K. C. (2022). An analysis of decomposition of consumption function between male and female households in India. *Journal of Public Affairs*, *22*(4), e2655. https://doi.org/10.1002/pa.2655

Raj, J., Gupta, V., & Shrawan, A. (2024). Economic Growth and Human Development in India – Are States Converging? *Indian Public Policy Review*, *5*(3 (May-Jun)), Article 3 (May-Jun). https://doi.org/10.55763/ippr.2024.05.03.004

Ravallion, M. (2012). Troubling tradeoffs in the Human Development Index. *Journal of Development Economics*, *99*(2), 201–209. https://doi.org/10.1016/j.jdeveco.2012.01.003

Ringen, S. (1991). Households, Standard of Living, and Inequality. *Review of Income and Wealth*, *37*(1), 1–13. https://doi.org/10.1111/j.1475-4991.1991.tb00335.x

Sala-i-Martin, X. X. (1996). Regional cohesion: Evidence and theories of regional growth and convergence. *European Economic Review*, *40*(6), 1325–1352. https://doi.org/10.1016/0014-2921(95)00029-1

Sen, A. (1985). *Commodities and Capabilities*. Oxford University Press India.

Sen, A. (2001). The many faces of gender inequality. *New Republic*. https://www.semanticscholar.org/paper/The-many-faces-of-gender-inequality-Sen/4dbdacea57a3695ed0a1816cdeb69525617cdbed

Srinivasan, T. N. (1994). Human Development: A New Paradigm or Reinvention of the Wheel? *The American Economic Review*, *84*(2), 238–243.

United Nations Development Programme. (1995). *Human Development Report 1995*. United Nations Development Programme (UNDP).

United Nations, European Commission, International Monetary Fund, Organisation for Economic Co-operation and Development, & World Bank. (1993). *System of National Accounts*.

Usher, D. (1973). *An imputation to the measure of economic growth for changes in life expectancy* (pp. 193–232). National Bureau of Economic Research.

Waring, M. (2003). Counting for something! Recognising women's contribution to the global economy through alternative accounting systems. *Gender & Development*, *11*(1), 35–43. https://doi.org/10.1080/741954251

Wolff, H., Chong, H., & Auffhammer, M. (2011). Classification, Detection and Consequences of Data Error: Evidence from the Human Development Index. *The Economic Journal*, *121*(553), 843–870. https://doi.org/10.1111/j.1468-0297.2010.02408.x

World Bank. (2024). *World Development Indicators*. World Bank.

Yagihashi, T., & Du, J. (2023). Intertemporal elasticity of substitution with leisure margin. *Review of Economics of the Household*, *21*(4), 1473–1504. https://doi.org/10.1007/s11150-022-09639-1

Technical Appendix

Table 2. Classification of states based on the NSDP per capita in 1981

Category	**States**
Poorest	Uttar Pradesh (UP), Bihar (BR), Rajasthan (RJ), Odisha (OD)
Lower-middle	Andhra Pradesh (AP), Kerala (KL), Assam (AS), Madhya Pradesh (MP)
Upper-middle	Karnataka (KA), Tamil Nadu (TN), West Bengal (WB)
Richest	Gujarat (GJ), Maharashtra (MH), Haryana (HR), Punjab (PB)

Construction of Lifetables

We explain the key methods undertaken for the construction of survival rates in detail, and specific data assumptions, along with providing supplementary information on the full income growth, wherever necessary.

We use the age-specific mortality rates provided by the Sample Registration System (SRS), administered by the Office of the Registrar General and Census Commissioner, to construct life tables. The purpose of constructing the life tables is to arrive at the yearly survival rates for each age and the years 1981, 1991, 2001, 2011, and 2019. The SRS compendium 1997-2013 has mortality rates for the age intervals 0-4, 5-9, 10-14, and so on. However, the mortality rates of the 0-4 age interval needed to be disaggregated into 0-1 and 1-4, due to a significant number of deaths often being concentrated in the 0-1 bracket (Hossain et al., 2023; Singh et al., 2017). Hence, we wanted to capture this nuance to produce more accurate yearly survival rates.

Fergany's Method

Fergany's method was used to disaggregate the mortality rate of the age interval, 0-4 years (Fergany, 1971). We first assumed that the Infant Mortality Rate (IMR) data obtained from the SRS was the age-specific mortality rate for the age group 0-1 years. We then used Fergany's method to calculate the ASMR for the 1-4 age group. Based on Fergany's method, the ASMR for different age intervals is converted to the probability of dying between ages 1 and 4, denoted here by q_{1-4}. q_{1-4} is calculated as $1 - p_{1-4}$, where p_{1-4} is the probability of surviving between ages 1 to 4. Since p_{1-4} is not provided for this age interval (due to no ASMR data for ages 1-4), we calculate p_{1-4} as the conditional probability i.e. $\frac{p_{0-4}}{p_{0-1}}$. This denotes the probability of surviving between ages 1 to 4 given that the child has already survived the first year. p_{0-4} is the probability of surviving between ages 0 to 4, and p_{0-1} is the probability of surviving between ages 0 to 1.

Once, p_{1-4} and q_{1-4} are calculated, we use Fergany's method to calculate the ASMR for ages 1-4 by the following equation (Fergany, 1971):

$$q_{1-4} = 1 - e^{-n*ASMR_{1-4}}$$

Where 'n' is the timeframe of the age interval and in this case, *n* is 4 years.

We rearranged this equation to compute $ASMR_{1-4}$, yielding the following expression:

$$ASMR_{1-4} = -\frac{1}{n} ln(1 - q_{1-4})$$

The mortality rates for the age group 1-4 for the 15 major states were similarly calculated with the gender segregation.

Forecasting Mortality Rates for Ages 70+

Once the ASMR for age groups 1-4 were calculated for all the states and both genders, we used different methodologies to test for the closest match of the life expectancy at birth (LEB) with the values provided in the 2016-2020 abridged life table report by the SRS. These methods are also used to calculate the age-specific mortality rates of the age groups 70-74, 75-79, 80-84, 85-89, 90-94, and 95+ as the SRS compendium (1997-2013) report only provides the mortality rate aggregated at the 70+ age group. Four methods were used to calculate mortality rates for the 70+ age groups: (1) the Gompertz Model (2) the Smoothing method using a three-point average (3) Constant exponential growth (4) Linear Extrapolation.

Gompertz Model

The Gompertz Model is based on the Gompertz Law of Human Mortality first described in 1825 by Benjamin Gompertz. The law suggests that the risk of dying (mortality rate) increases exponentially as the age of an individual increases (Gompertz, 1997). It is given by $m_x = Ae^{bx}$, where m_x is the age-specific mortality rate, or in this case, the age-specific mortality rate at age 'x'. 'A' is the baseline mortality rate and 'b' is the rate at which the mortality increases. The baseline mortality rate is the initial mortality rate before the exponentiation occurs.

$$ln(mx) = a + bx$$

(1) We use the mortality rates for the age groups 30-34, 35-39 till 65-69 years to fit the Gompertz curve and derive the mortality rates for the age groups 70-74, 75-79 till 95+ or 100.

(2) We used an exponential regression model using the LINEST function in Microsoft excel. Each ASMR for each age up until the age interval of 65-69, was log-transformed as $ln(ASMR_{x,1981})$ where x is the age interval for the particular year.

(3) For the calculation of the regression line parameters i.e. slope 'b' and intercept 'a', we used the formula $= LINEST(LN(M11{:}M18), C11{:}C18, TRUE, TRUE)$

(4) We projected the ASMR for the age groups of 70+ and beyond based on the estimated regression parameters $ASMR_{70-74} = e^{(b \times n + a)}$, where n is the mid-point of that particular age interval (in this case, 72.5 years)

Constant Exponential Function

We also projected the mortality rates for ages 70 and with the constant exponential growth based on the last few age groups. This method differs from the Gompertz as we did not use the mortality rates from ages 30, but instead calculated the growth factor based on the logarithmic differences of the mortality rates of the last two age groups i.e. 60-64 and 65-69 (Lee and Carter, 1992). The growth factor was calculated by first taking the difference in the logarithm of the mortality rates and then dividing this difference by the timeframe i.e. the difference in the mid-points of these two age intervals (62.5 and 67.5). This growth factor was then exponentiated and multiplied by the difference in the mid-points of the age intervals 65-69 and 70-74 (67.5 and 72.5 respectively). This method was applied progressively to forecast mortality rates for each subsequent age group, continuing until the age intervals above 95. The following equation was used to compute the *growth factor.*

$$growth\ factor, r\ = \frac{ln(ASMR_{70-74}) - ln(ASMR_{65-69})}{t2 - t1}$$

Where $t2$ is the mid-point of the age interval 65-69, and $t1$ is the mid-point of the age interval 60-64.

$$ASMR_{70-74}\ = ASMR_{65-69}\ .\ exp(r.(t3 - t2))$$

Where $t3$ is the mid-point of the age interval for which the ASMR needs to be forecasted i.e. 70-74, and $t2$ is the mid-point of the previous age interval i.e. 67.5 for the age group 65-69.

Three-Year Moving Average

A simple three-year moving average method was also used as another method to forecast the mortality rates of ages 70 years and beyond. For each age group, the average death rate of the current age interval and its consecutive groups (before and after), was computed eg. 30-34, 35-39, and 40-44. This is considered one of the smoothing techniques to account for data anomalies or fluctuations (APHEO, 2024; Chatfield, 2004). The average of the changes or slopes between two consecutive average rates was calculated. This average of all the slopes was used as the growth factor to extrapolate the mortality rates for age intervals 70-74, and so on.

For example, the three-year moving average of the age group 50-54 would be:

$$\frac{ASMR_{45-49} + ASMR_{50-54} + ASMR_{55-59}}{3}$$

Once these averages were calculated, we computed the slopes between these averages:

(Moving Average$_{50\text{-}54}$ - Moving Average$_{45\text{-}49}$)/2

$$\frac{Moving\ Average_{50-54} - Moving\ Average_{45-59}}{2}$$

The average of all these slopes was used as the rate of change and growth factor to forecast the ASMR of age groups 70-74 and beyond as specified in the following equation:

Linear Extrapolation

We calculated the growth factor by assuming linear growth in the mortality rates towards the higher age groups. The growth factor, r was computed as follows:

Growth factor $r = \frac{(ASMR_{65-69} - ASMR_{60-64})}{(t2 - t1)}$

where $t2$ is the mid-point of the age interval 65-69 and $t1$ is the mid-point of the age interval 60-64.

$$ASMR_{70-74} = ASMR_{65-69} \times exp(r \times (t3 - t2))$$

Where $t3$ is the mid-point of the age interval for which the ASMR needs to be forecasted i.e. 70-74, and $t2$ is the mid-point of the previous age interval i.e. 67.5 for the age group 65-69.

Accounting for State Reorganization

Chhattisgarh, Jharkhand, and Uttarakhand were separated from the states of Madhya Pradesh, Bihar, and Uttar Pradesh respectively in 2000. Hence, our analysis combined the life tables for the states of Chhattisgarh, Jharkhand, and Uttarakhand with their parent states for the years 2001, 2011, and 2019 to produce ASMR for the undivided states. Similarly, Telangana was separated from Andhra Pradesh (AP) in 2014, so we combined AP and Telangana's life tables for the year 2019. A population-weighted approach was undertaken where the mortality rates were weighted by the states' overall populations. The underlying assumption is that the population distribution across age groups is similar for both the states i.e. the parent state and the divided state.

The earliest available SRS data on the ASMR for Jharkhand and Chhattisgarh were from 2004. Hence, we used the 2004 population-weighted ASMR data for these two states and combined them with the 2001 population-weighted ASMR data for their parent states, Bihar and Madhya Pradesh. The age-specific death rates for Uttarakhand were available for the year 2001, so we used those as is for the combined life table computation.

Data Limitations

(1) The mortality rate for the 1-4 age group in Kerala, calculated from the IMR (0-1 years), and the overall mortality rate for 0-4 years from SRS India data, resulted in a non-existent or near-zero rate. This could imply that most/all of the deaths were concentrated in the 0-1 group.

(2) The Gompertz model used to extrapolate mortality rates for older age groups exhibited overfitting for the state of Assam in 1981 (male), resulting in mortality rates exceeding 1 (e.g. 1.03 for the 95+ age group). Hence, for generating the survival rates gender-wise in Assam, the average three-point smoothing method was instead used as this method did not lead to negative survival rates in the age group 95+. The three-point method for Assam also yielded life expectancy values closer to those observed in the abridged SRS 2016-20 report.

Construction of Yearly Discounted Survival Rates

The yearly survival rates were constructed using standard lifetable techniques as in demography studies with the presented ASMR in the SRS compendium (1971 to 2013). Once the mortality rates for the age groups of 70-74 and above were projected, the ASMR was used to construct the yearly survival rates with the following technique:

(1) The mortality rate for an age interval was assumed to be similar for all ages eg. $ASMR_{1-4}$ is the same for each age i.e. 1, 2, 3, and 4 years. This was categorized as the ASMR for each age, denoted by q_x , where x is the particular age.

(2) The survival probability for age $x+1$, denoted by p_{x+1} was calculated as $p_x(1- q_x)$

(3) The probability of surviving exactly till age $x+1$ denoted by n_{x+1} was computed as $p_{x+1} \times (x+1)$, and the life expectancy as $e_{x+1} = n_{x+1} \times (x+1)$

(4) The life expectancies for all ages were then summed to determine the life expectancy at birth (LEB)

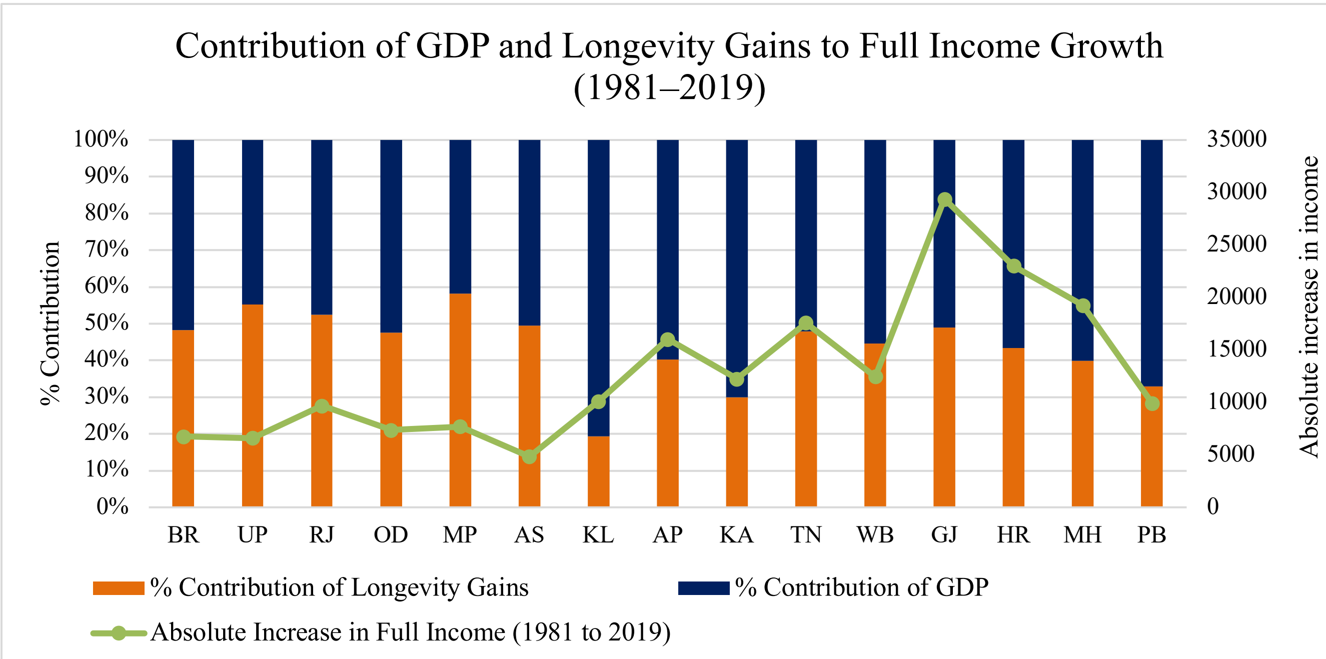
(5) With the values of $\delta = 1.25$, $\alpha = -14.97$, and $r = 0.03$, the discount factor for each age x was calculated as $d_x = (1+r)^{-x}$

(6) The discounted survival function for each year and each age was computed as $Sr_{x,1981} = d_x \times p_{x,1981}$ where $p_{x,1981}$ is the survival probability of age x in the year 1981.

(7) $A(t)$ as given in Becker et al.'s (2005) is calculated as $A(t) = \Sigma Sr_{x,1981}$

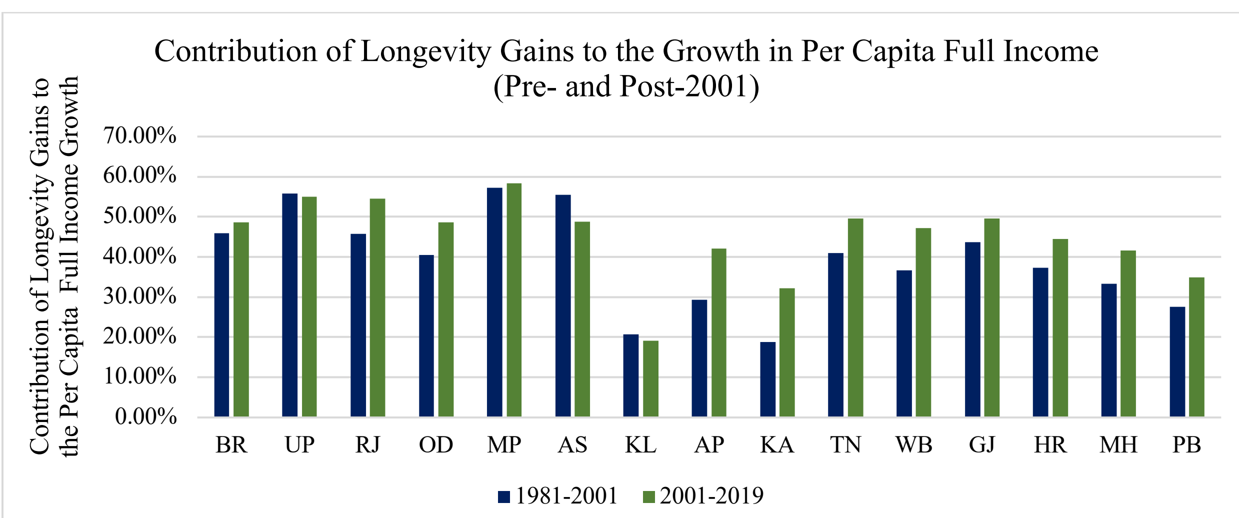
Supplemental Figures and Tables

Figure 9. Contribution of Longevity Gains and GDP to Full Income Growth (State-wise), 1981-2019



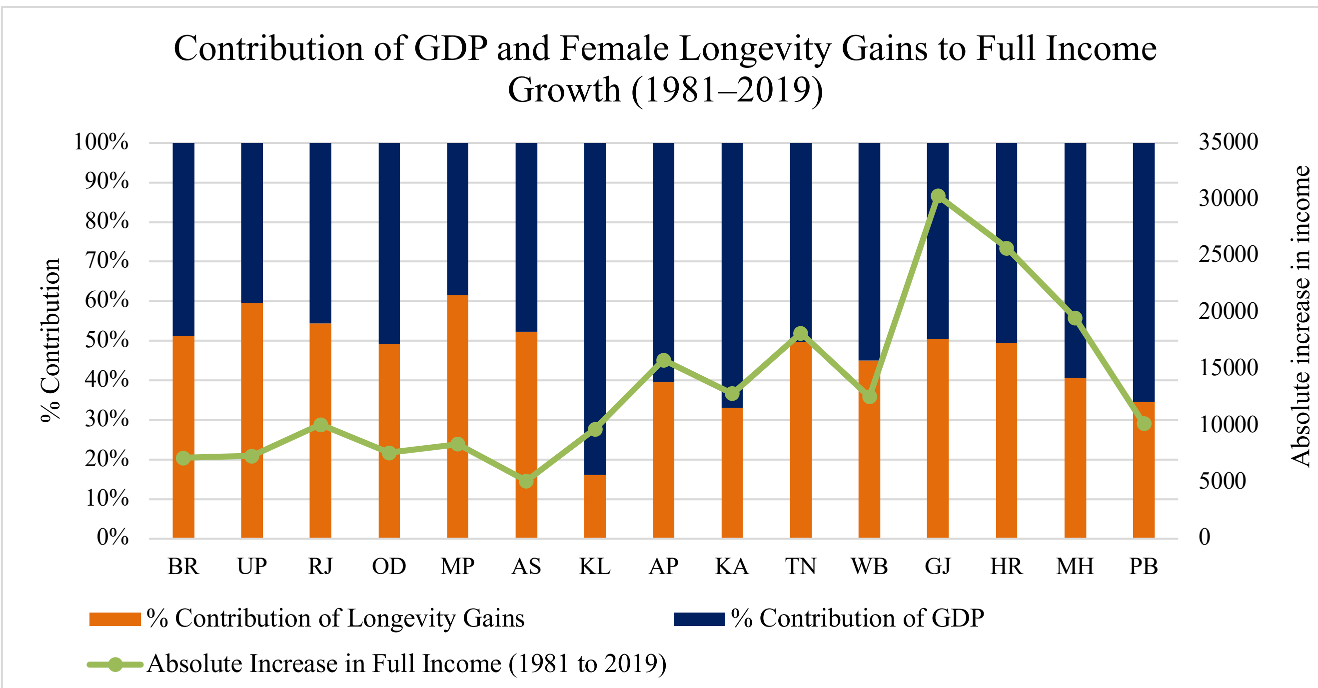
Source: Authors' estimates

Figure 10. Inter-state performance of longevity gains pre- and post-2001



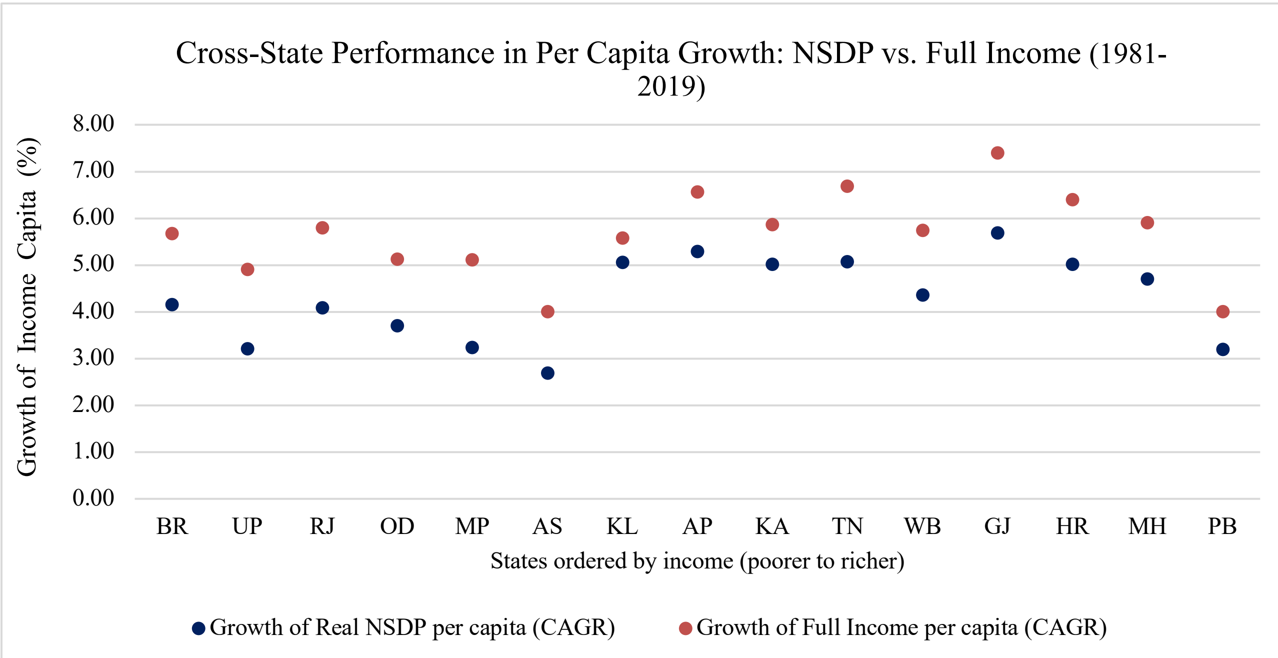
Source: Authors' estimates

Figure 11. Contribution of Female Longevity Gains and GDP to Full Income Growth (State-wise with Gender Segregation), 1981-2019



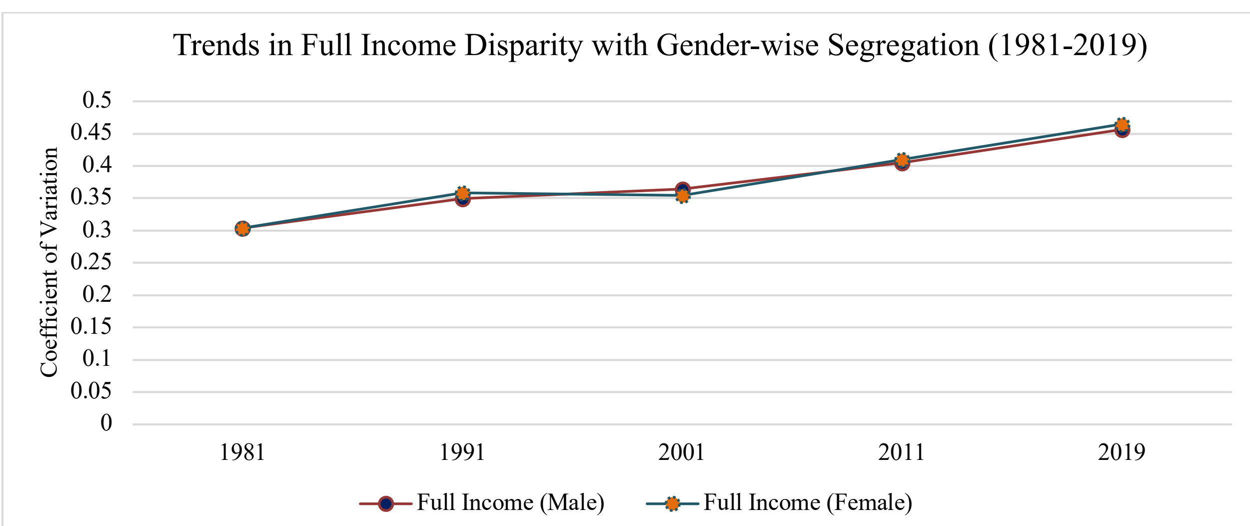
Source: Authors' estimates

Figure 12. Per Capita Growth Rate of Full Income Measure and Pure Income Measure, 1981 to 2019 (State-wise)



Source: Authors' estimates

Figure 13. The dispersion of full income per capita across Indian states (gender segregation), 1981 to 2019



Source: Authors' estimates

Table 3. State-wise Monetary Values of Longevity Gains for Females versus Males (1981 to 2019) in INR per capita

	Male	**Female**
Uttar Pradesh	3013	4360
Rajasthan	4456	5500
Haryana	7476	12696
Punjab	2954	3515
Andhra Pradesh	6170	6237
Kerala	2203	1567
Karnataka	3369	4242
Tamil Nadu	7790	9031
Gujarat	13383	15325
Maharashtra	7060	7933
Odisha	3231	3744
West Bengal	5456	5653
Assam	2107	2678
Bihar	2872	3660
Madhya Pradesh	3845	5142

Source: Authors' estimates

Table 4. Coefficient of Variation with Gender Segregation

Year	Overall (Pure Income)	Overall (Full Income)	Full Income (Female)	Full Income (Male)
1981	0.30	0.30	0.30	0.30
1991	0.35	0.35	0.36	0.35
2001	0.37	0.36	0.35	0.36
2011	0.41	0.41	0.41	0.41
2019	0.46	0.46	0.46	0.46

Source: Authors' estimates

Table 5. Testing for Life expectancy Beta Convergence

	Rate of Growth (1981-2001)	Rate of Growth (2001-2019)
Life Expectancy_1981	-0.0158^{***}	
	(0.00344)	
Life Expectancy_2001		-0.0208^{**}
		(0.00536)
_cons	1.328^{***}	1.658^{***}
	(0.192)	(0.346)
R-squared	0.619	0.537

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Monetary Values of Longevity Gains (1981-2019) under different IES for the Poorest & Richest States

State	**Classification**	**Uniform IES of 1.25 & Alpha= -14.97**	**IES=0.8 & Alpha=0.59 for the Poorest States**	**IES=0.5 & Alpha=0. 0002 for the Poorest States**	**IES=0.5 for the Poorest States, IES=0.8 for the other States**	**Uniform IES of 2.2 & Alpha=221.34**
Andhra Pradesh	Lower-Middle	6440.149	6440.149	6440.149	5404.406	7187.334
Assam	Lower-Middle	2389.949	2389.949	2389.949	697.1236	4821.549
Bihar	Poorest	3263.795	1163.845	-126.0146	-126.0146	5943.657
Gujarat	Richest	14383.01	14383.01	14383.01	17006.14	12968.97
Haryana	Richest	9978.23	9978.23	9978.23	10540.93	9608.979
Karnataka	Upper-Middle	3658.132	3658.132	3658.132	2819.677	4361.396
Kerala	Lower-Middle	1957.597	1957.597	1957.597	1435.483	2437.45
Madhya Pradesh	Lower-Middle	4467.934	4467.934	4467.934	1628.573	7876.797
Maharashtra	Richest	7682.893	7682.893	7682.893	7484.409	7792.181
Odisha	Poorest	3504.261	1163.845	37.89364	37.89364	5826.554
Punjab	Richest	3268.348	3268.348	3268.348	2406.284	4022.963
Rajasthan	Poorest	5079.302	1163.845	308.3842	308.3842	7695.953
Tamil Nadu	Upper-Middle	8427.888	8427.888	8427.888	7074.077	9336.289
Uttar Pradesh	Poorest	3644.974	1163.845	-186.2152	-186.2152	6810.298
West Bengal	Upper-Middle	5549.343	5549.343	5549.343	3854.541	6964.693

Source: Authors' estimates