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Abstract

India's demographic dividend — the temporary growth bonus that arises when a country's working-age population expands faster than its dependent population — represents one of the most consequential economic opportunities in modern development history. With over 900 million people between the ages of 15 and 64, a total fertility rate that has declined to near-replacement level, and an age dependency ratio that has fallen from 64% to approximately 48% over the first quarter of the twenty-first century, India entered and sustained its demographic window during precisely the period in which its economy was completing three decades of post-liberalisation structural transformation. Whether that coincidence of demographic advantage and economic reform translated into a fully realised dividend — or whether the opportunity was fragmented, unevenly distributed, and substantially wasted — is the question this study sets out to answer.

Existing scholarship on India's demographic dividend has been conducted predominantly through single-variable frameworks: working-age population growth rates regressed against GDP per capita growth, dependency ratios correlated with savings rates, or state-level demographic variation mapped against industrial output. These approaches generate important findings, but they are structurally unable to capture the multi-dimensional conditionality of the dividend — the fact that demographic scale alone cannot produce sustained, broad-based development unless it is simultaneously supported by human capital quality, effective labour market absorption, social equity, and macroeconomic stability. This study addresses that gap by constructing a comprehensive, original, multi-index empirical framework applied to India across the period 2000–2024.

The methodological contribution of the study is the construction of six composite indices — the Demographic Structure Index (DSI), the Demographic Quality Index (DQI), the Harnessing Capacity Index (HCI), the Social Development Index (SDI), the Macroeconomic Variables Index (MVI), and the Economic Growth Index (EGI) — each built from ten annual time-series indicators using the OECD Handbook methodology of Nardo et al. (2008). All sixty indicators are drawn from primary data sources including the World Bank World Development Indicators, MoSPI National Accounts Statistics, ILO modelled labour market estimates, the Reserve Bank of India's Handbook of Statistics, NCRB crime data, and DPIIT FDI statistics. Each index is constructed through a standardised eight-step process: framework definition, data selection, direction alignment, Z-score normalisation, constant shifting for strict positivity, Principal Component Analysis (PCA) for data-driven weighting using Kaiser criterion eigenvalue selection, and PCA-weighted geometric mean aggregation.

The geometric mean design ensures partial non-compensability — a year of strong performance on one dimension cannot fully offset weakness on another — making each index a genuinely multi-dimensional composite rather than a weighted average that disguises dimensional trade-offs.

The five independent indices — DSI, DQI, HCI, SDI, and MVI — are then submitted to an Ordinary Least Squares regression against the EGI as the dependent variable, with HC1 heteroskedasticity-consistent robust standard errors applied throughout to ensure valid inference. The model explains 75.5% of the annual variation in India's composite economic growth performance ($R^2 = 0.755$, adjusted $R^2 = 0.686$, $F = 11.75$, $p < 0.001$). Residuals are normally distributed (Shapiro-Wilk $p = 0.817$) with no significant serial correlation confirmed via Breusch-Godfrey and Ljung-Box tests, and Variance Inflation Factors confirm that multicollinearity does not fatally compromise the coefficient estimates.

The regression results constitute the study's central empirical contribution. Two of the five independent indices achieve statistical significance at the 1% level, and their findings together define the Indian paradox. The Demographic Structure Index carries a coefficient of +4.10 ($p < 0.01$) — the largest in the model — confirming that India's structural demographic transition has been the dominant engine of its economic growth over the study period. The working-age population expansion, falling dependency burden, declining fertility, and rising urbanisation that the DSI captures have generated real, measurable, statistically robust growth benefits across all ten dimensions of the EGI composite. This finding validates the foundational theoretical prediction of Bloom and Williamson (1998) and extends it to a twenty-five-year composite index framework specific to India.

The Demographic Quality Index carries a coefficient of −3.40 ($p < 0.01$) — equal in statistical strength to the DSI but diametrically opposite in sign. This is the study's most provocative and most important result. A rising DQI — reflecting improvements in life expectancy, mean years of schooling, immunisation coverage, child nutrition, adult literacy, maternal health, and educational enrolment across secondary, tertiary, and vocational pathways — is associated with *lower* multi-dimensional economic growth performance in the same year, not higher. This negative relationship, which is structurally consistent with and precisely quantifies the "jobless growth paradox" identified by Drèze and Sen (2013) in their qualitative analysis of India's development failure, reveals that India's investment in human capital has not been wasted in the sense of failing to improve people's capabilities. It has been wasted in the more consequential economic sense: the capabilities being built are not being absorbed into productive employment. Better-educated and healthier workers are entering a labour market defined by skill mismatches, formal sector scarcity, and institutional inadequacy, and the economic system is failing to convert their improved human

capital into the investment, industrial output, trade integration, and financial deepening that a fully realised demographic dividend would produce.

The three remaining indices — HCI (+0.56), SDI (−0.23), and MVI (+0.19) — are not statistically significant at conventional thresholds. The positive signs on HCI and MVI are directionally consistent with theory, confirming that labour market activation and macroeconomic stability are associated with higher growth, but their magnitudes are insufficient to register as independent growth drivers in a model dominated by the opposing demographic forces. The SDI's near-stagnation — with a coefficient of variation of just 6.3% across the twenty-five-year period — means that India's social equity framework has barely moved, making it structurally unable to explain variation in economic growth outcomes.

The study draws three broad conclusions. India has captured the first demographic dividend — the mechanical growth benefit of working-age expansion — but has largely failed to build the second demographic dividend, which requires converting human capital investments into sustained productivity growth through effective labour market absorption. The quality dimension of the demographic opportunity has been fragmented by three compounding structural failures: an education and skills system that expands enrolment without producing employment-relevant competencies; a manufacturing and industrial policy framework that has presided over structural deindustrialisation rather than the labour-intensive industrial transformation that East Asian economies achieved during their own demographic windows; and a social equity architecture that has left women — constituting half the demographic dividend — systematically excluded from formal economic participation. The demographic window is time-bound. India's old-age dependency ratio will begin rising by the mid-2040s, and when the structural contribution of the DSI diminishes, sustained growth will require the total factor productivity gains that only a well-absorbed, productively employed, and socially inclusive workforce can generate. The policy imperative — to pivot education toward employability, to scale labour-intensive manufacturing and agro-processing, and to implement the structural labour market reforms embodied in the four Labour Codes — is not a long-run aspiration. It is an urgent, time-constrained obligation, and the DQI's coefficient of −3.40 is its quantified measure of the cost of continued delay.

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This thesis took longer and asked more of me than I had expected. I could not have finished it without the people I want to mention here.

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Chapter 1
Introduction

1.1 The Question That Demands an Answer

Something does not quite add up about India's economic story over the last two and a half decades. Between 2000 and 2024, India's GDP per capita grew at an average annual rate of around 5.5 percent, making it one of the fastest-growing large economies in the world (World Bank, World Development Indicators, 2024). Its working-age population, defined as those aged 15 to 64 years, rose from roughly 60 percent of total population in 2000 to 68.2 percent by 2024, which in absolute numbers represents a working-age cohort of approximately 990 million people (World Bank, WDI Series SP.POP.1564.TO.ZS, 2024; UNFPA India Parliamentary Data, 2025). The country's total fertility rate fell from around 3.4 births per woman in the late 1990s to 1.9 births per woman by 2023, falling below the replacement threshold of 2.1 for the first time in the nation's recorded demographic history (Office of the Registrar General of India, SRS Statistical Report, 2023). Infant mortality dropped from approximately 65 to 70 deaths per 1,000 live births around 2000 to 25 deaths per 1,000 live births by 2023, representing a decline of more than 60 percent over the period (SRS Bulletin, Vol. 58, 2023). The urban share of the population climbed from around 27.8 percent in 2001 to roughly 35 percent by 2024, and is projected to reach over 40 percent by 2030 as tens of millions of rural workers continued to migrate toward cities (Economic Survey 2023-24; World Bank Urban Development Report, 2024).

By almost every demographic measure, India appeared to be entering the window that economists and demographers call the demographic dividend. The conditions were aligning in the way the textbooks said they would. And yet, when one looks at the other side of this story, a far more complicated picture emerges. Millions of educated young people remained unable to find formal employment. Female labour force participation fell even as women's educational attainment improved. Child malnutrition, gender-based violence, and deep social exclusion persisted through years of 7 and 8 percent GDP growth. India was growing, clearly. But the question of whether it was developing in any meaningful, broad-based sense remained genuinely open.

This is not just an academic puzzle. It touches the lives of hundreds of millions of people who are not old enough to remember the pre-reform era, who have grown up in a country that told them education was the path to prosperity, and who are now discovering that the economy has not prepared a place for many of them. The gap between India's demographic potential and its institutional delivery is one of the most

consequential development questions of the twenty-first century, and it deserves a more rigorous and more honest analytical treatment than it has usually received.

This dissertation begins with that tension. Its central question is simple to state but demanding to answer properly: has India effectively harnessed its demographic dividend? To answer it honestly requires first acknowledging a problem with how this question has usually been approached. The demographic dividend is almost always studied through one or two aggregate demographic ratios, typically the working-age share or the dependency ratio, regressed against GDP growth. That approach can tell us whether favourable age structure is correlated with faster growth. It cannot tell us whether India's demographic opportunity is being realised broadly or narrowly, whether the quality of the population matters alongside the quantity, whether the institutions needed to absorb labour are working, or whether social exclusion is fragmenting the dividend before it reaches the majority of people.

This dissertation proposes a different approach. It argues that the demographic dividend operates through at least five distinct channels: the structural age composition of the population, the health and education quality of that population, the capacity of labour markets and institutions to absorb the working-age cohort productively, the social equity conditions under which demographic change is happening, and the macroeconomic environment in which all of this plays out. Each of these channels must be measured separately, with care and theoretical rigour, before they can be integrated into a unified model. Only then can one begin to answer, with any precision, whether India's dividend has been fulfilled, partially captured, or systematically lost.

1.2 India at a Demographic Crossroads

To appreciate why this question matters, it helps to understand what the demographic dividend actually means and why India's position is historically significant. The concept traces back to the work of Frank Notestein (1945), who first described the demographic transition as a society's passage from a state of high fertility and high mortality to one in which both are low. During the middle phase of this transition, mortality falls first and fertility follows later. The gap between the two creates a temporary surge in the working-age share relative to dependants. This is the window of opportunity.

The economic consequences of that window were most powerfully demonstrated by Bloom and Williamson (1998) in their study of East Asia's economic miracle. They found that East Asia's demographic transition resulted in its working-age population growing at a much faster rate than its dependent population during 1965 to 1990, thereby expanding the per capita productive capacity of East Asian economies. Their estimate was that demographic change accounted for between one-quarter and two-

fifths of East Asia's growth during that period. The central insight was that it was the structure of the population that mattered, not its size or raw growth rate. When the share of workers relative to dependants rises, productive capacity expands, savings rates tend to increase, and per capita incomes can grow even without any change in technology or institutional quality.

India's dividend window opened later than East Asia's but is no less significant. Aiyar and Mody (2011), in their IMF Working Paper on the Indian states, found that there is a large and significant growth impact of both the level and growth rate of the working-age ratio, with demographic change accounting for between 40 and 50 percent of India's growth acceleration since the 1980s. More recent data from the World Bank confirms that India's working-age share rose from around 60 percent in 2000 to 68.2 percent in 2024 (World Bank, WDI, 2024). The working-age population is now approximately 68.7 percent of a total population of 1.46 billion, giving India the largest working-age cohort of any nation on earth (UNFPA India Parliamentary Data, 2025).

But Lee and Mason (2006) were equally clear that this window is temporary and conditional. In their widely cited note in Finance and Development, they wrote that with fewer people to support, a country has a window of opportunity for economic growth if the right social and economic investments and policies are made. The word "if" carries enormous weight in that sentence. The demographic dividend has never been automatic. It depends on what a country does with its structural advantage. Countries that built the institutions, invested in education and health, opened their economies, and created the conditions for labour absorption captured large dividends. Countries that did not, lost the opportunity. India's position today is precisely at this fork in the road, and the evidence on both sides of the argument is strong enough to make the answer genuinely uncertain.

Notestein's (1945) four-stage model of the demographic transition begins with a pre-modern state of high fertility and high mortality, moves through a phase where mortality declines but fertility remains high, then enters a transitional period where fertility finally falls, and culminates in a low-fertility, low-mortality equilibrium. India, in 2000, was firmly in the third stage. The country's total fertility rate had been declining for several decades, driven by family planning programmes, rising female literacy, and urbanisation, all of which are documented extensively in the NFHS series (NFHS-3, 2005-06; NFHS-4, 2015-16; NFHS-5, 2019-21). The IMR, which Barro and Sala-i-Martin (2004) identify as a demographic driver of fertility through the child survival hypothesis, fell sharply across the same period, from approximately 65 to 70 per 1,000 live births around 2000 to 25 per 1,000 by 2023 (SRS Bulletin, 2023). As families became confident their children would survive, desired family size fell, reinforcing the fertility decline and compressing the youth dependency ratio.

What happened next was precisely the structural shift that demographic dividend theory predicts. The large cohorts born during the high-fertility era of the 1970s and 1980s were entering the working-age band by the early 2000s, swelling the working-age share. At the same time, the smaller cohorts being born in the 1990s and 2000s were reducing the child dependency burden. The total dependency ratio, which measures the number of dependants per 100 working-age persons, has been declining steadily over this period and is projected by the MoSPI Technical Group to fall from 65 in 2011 to 54 by 2036 (National Commission on Population, Technical Group Population Projections, 2020). The structural conditions were, in the language of Bloom, Canning, and Sevilla (2003), aligned in a way that had created enormous potential for economic acceleration.

1.3 The Problem with Existing Approaches

The empirical literature on India's demographic dividend has made genuinely important contributions, but it shares a set of methodological limitations that this dissertation tries to address. The most common approach is to take one or two demographic variables and regress them against GDP growth. Choudhry and Elhorst (2010), for example, found that population dynamics explained approximately 39 percent of per capita GDP growth in India over 1961 to 2003, using the growth differential between the working-age population and total population as the key demographic variable. Bloom, Canning, Fink, and Finlay (2007) showed that age structure variables significantly improve the forecasting of economic growth. Aiyar and Mody (2011) demonstrated the Indian state-level evidence for the same mechanism. These are important results, but they share a common limitation: they treat the dividend as if it were a single-channel phenomenon driven entirely by the numerical shift in age composition.

The problem is not that this approach is wrong. The working-age share does drive growth. Dependency ratios do matter. Fertility decline does improve savings potential. All of this is empirically robust. The problem is that this approach cannot distinguish between a country that is harnessing its dividend broadly and one that is extracting narrow aggregate growth while leaving the majority of the population's capabilities unrealised. It treats all growth as equivalent, whether it comes from highly productive formal employment or from vast pools of informal, low-productivity work that keep hundreds of millions of workers technically employed but deeply underutilised.

Kelley and Schmidt (1995), in their study of 89 countries over 1960 to 1995, introduced an important corrective to this view. They showed that the positive impacts of a large working-age cohort could be swamped by the costs of rearing children and maintaining an enlarged youth-dependency age structure if labour market conditions

are not right. This was an early warning that the dividend is not merely a function of age structure but of the whole institutional and social environment in which age structure change takes place. Their finding, that the results of omitting the composition of population dynamics can be seriously misleading, pointed toward the need for exactly the kind of multidimensional framework this dissertation constructs.

The broader development literature has long argued that the conflation of growth with development is untenable. Amartya Sen (1999) argued in Development as Freedom that development must be understood as the expansion of real freedoms people can actually enjoy, not merely as the growth of GDP. His capability approach insists that the metrics of development must include health, education, political participation, and social equity alongside income. Dreze and Sen (2013), in An Uncertain Glory, showed with detailed empirical evidence that India's high growth rates between 2000 and 2013 coexisted with some of the worst social indicators among countries at comparable income levels. They described this as an asymmetry between India's economic growth and its social indicators, and they documented it systematically across health, education, gender equity, and nutrition. The growth was real. Its developmental reach was not.

The labour economics literature adds a further layer of critique. Lewis (1954), in his foundational dual-sector model, argued that development in poor countries proceeds through the reallocation of labour from low-productivity subsistence agriculture into high-productivity capitalist industry and services. The demographic dividend amplifies this process: a larger working-age cohort provides the surplus labour that can be redeployed into modern sectors. But this only works if the modern sector is actually creating jobs at the rate required to absorb the expanding cohort. Mehrotra, Parida, Sinha, and Gandhi (2014), using data from 1993-94 to 2011-12, demonstrated that despite high GDP growth during the period 2004-05 to 2011-12, the employment situation in India deteriorated, and the absolute number of workers actually declined significantly. The worker population ratio fell precisely during the period of India's fastest economic expansion. This is the phenomenon that the existing demographic dividend literature, focused exclusively on age structure, simply cannot see.

The gender dimension adds yet another layer. India's Female Labour Force Participation Rate, which measures the share of women either employed or actively seeking employment, declined sharply from approximately 32 percent in 2000 to below 23 percent by 2017-18, even as women's educational attainment was improving (ILO ILOSTAT; World Bank WDI Series SL.TLF.ACTI.FE.ZS). The OECD (2015) documented that in India, unlike in most economies, education and income are negatively correlated with female labour force participation: more educated women withdraw from low-skill jobs but face social and structural barriers to entering high-skill employment. Mehrotra et al. (2017) showed through empirical analysis that the

income effect, rising household non-labour income, was the primary driver of declining Female LFPR, not GDP growth per se. Abraham (2013) showed that it is not economic growth but rather the composition of growth that matters for women: the de-feminisation of India's workforce was structural, driven by which sectors were growing, not how fast. These findings collectively establish that half of India's working-age population, its women, were being systematically excluded from the dividend, and that existing single-variable frameworks were structurally incapable of capturing this exclusion.

What the literature lacks is a unified empirical framework that measures both the structural demographic opportunity and the multiple conditions that determine whether it converts into genuine development. Demographers study age structure. Labour economists study employment quality. Sociologists study gender gaps. Macroeconomists study fiscal and monetary conditions. Each discipline captures one channel in isolation. None of them model all five channels together in a way that allows one to see which conditions are doing the most work and which are failing most obviously.

The OECD Handbook on Constructing Composite Indicators (Nardo, Saisana, Saltelli, Tarantola, Hoffmann, and Giovannini, 2008) provides the methodological tools to build exactly this kind of integrated framework. The Handbook explicitly states that the construction of composite indices requires a theoretical framework that defines the phenomenon to be measured and ensures that the set of individual indicators is selected based on their analytical soundness, measurability, country coverage, relevance to the phenomenon being measured and relationship to each other. By constructing theoretically grounded composite indices for each channel of the dividend process and estimating their joint relationship with a composite measure of economic growth, it becomes possible to see the demographic dividend as a system of interacting conditions rather than a single mechanism.

1.4 The Study's Analytical Framework

This dissertation constructs six composite indices for India over 2000 to 2024 and tests their joint relationship through a time-series OLS regression model. The six indices are the Demographic Structure Index (DSI), the Demographic Quality Index (DQI), the Harnessing Capacity Index (HCI), the Social Development Index (SDI), the Macroeconomic Variables Index (MVI), and the Economic Growth Index (EGI). Each index is built from ten carefully selected variables, each grounded in its own theoretical tradition and each individually justified on the grounds of theoretical soundness, causal directionality, and data availability for India over the study period.

The **Demographic Structure Index (DSI)** captures the structural age composition of India's population: working-age share, total and old-age dependency ratios, total fertility rate, crude birth and death rates, infant mortality rate, urbanisation share, sex ratio at birth, and annual population growth rate. Following Bloom and Williamson (1998) and Mankiw, Romer, and Weil (1992), this index treats age structure as the foundational demographic precondition for the dividend: the necessary but not sufficient opening condition. Every variable in the DSI has a multigenerational lag between its causes and its determination, which means its year-to-year values during 2000 to 2024 were set in motion by births, deaths, and migration decisions made decades earlier, establishing the DSI as causally prior to the contemporaneous economic outcome it is meant to explain.

The **Demographic Quality Index (DQI)** captures the health and education quality of India's population: life expectancy, mean years of schooling, child nutrition, immunisation coverage, adult literacy, maternal mortality, secondary and tertiary enrolment, and vocational training access. Bloom, Canning, and Sevilla (2003) showed that age structure alone is insufficient to drive development. The quality of the human capital within the working-age cohort determines whether demographic expansion translates into productivity growth or merely into larger pools of low-productivity labour. Psacharopoulos and Patrinos (2004) estimated that the social returns to primary education in the lowest-income countries average around 25 percent per year of schooling, establishing the theoretical link between education investment and development outcomes that the DQI is designed to track.

The **Harnessing Capacity Index (HCI)** captures India's labour market capacity to absorb its working-age population productively: total labour force participation, female labour force participation, worker-population ratio, share of regular salaried employment in total employment, informal employment share (inverted), labour productivity, employment elasticity of output, non-agricultural employment share, labour income share in GDP, and youth employment-to-population ratio. The HCI occupies the intermediate space between the quality of the human capital supply (DQI) and the ultimate economic outcome (EGI). It measures whether the available pool of workers is being channelled into employment, and whether the quality and structure of that employment relationship is productive. Lewis (1954) provides the theoretical foundation: in a dual-economy framework, development proceeds through the structural reallocation of labour from low-productivity agriculture into the capitalist sector, and the HCI tracks how far and how effectively this reallocation is happening. Besley and Burgess (2004) showed that labour regulation, not economic growth, is the primary determinant of formal employment creation in India, establishing HCI variables as institutionally rather than cyclically determined.

The **Social Development Index (SDI)** captures the social equity conditions under which the transition unfolds: maternal mortality, under-5 mortality, primary school enrolment, the Gender Inequality Index, female labour force participation, access to improved sanitation, the multidimensional poverty headcount, life expectancy at birth, consumption inequality (inverted Gini), and access to electricity. Sen (1999) and Dreze and Sen (2013) provide the philosophical and empirical backbone: development is the expansion of real capabilities, and the quality of social life is both an end in itself and a structural precondition for broad-based economic participation. The SDI draws on indicator series from the NFHS, the UNDP Human Development Reports, the SRS, the WHOUNICEF JMP, and NITI Aayog's National MPI calculations, covering the full range of social conditions that have been shown by Deaton (2003), Alkire and Seth (2008), and Preston (1975) to be causally prior to economic outcomes and not meaningfully responsive to short-run income fluctuations.

The **Macroeconomic Variables Index (MVI)** captures the enabling economic environment: inflation, fiscal deficit as a share of GDP, real interest rates, tax revenue as a share of GDP, public investment, general government debt, foreign exchange reserves, exchange rate competitiveness, financial sector health, and currency stability. Fischer (1993) established in his landmark study on the macroeconomics of economic growth that macroeconomic instability damages growth through both the capital accumulation channel and the productivity channel, making macroeconomic stability a structural prerequisite for converting demographic opportunity into realised economic performance. A country cannot harness its demographic dividend while fighting double-digit inflation, running unsustainable deficits, or managing recurrent balance of payments crises: the MVI is designed to capture the degree to which India's macroeconomic environment provided or denied that stable foundation over the study period.

Finally, the **Economic Growth Index (EGI)** serves as the dependent variable: a composite measure of India's realised economic growth performance spanning real GDP per capita growth, gross capital formation, trade openness, net FDI inflows, industrial production, manufacturing value added, financial depth, savings rates, household consumption, and total factor productivity. By constructing a multidimensional outcome measure rather than using GDP per capita growth alone, the study ensures the dependent variable is analytically rich enough to capture the breadth of economic expansion rather than a single narrow indicator.

The core empirical model is:

EGI = f(DSI, DQI, SDI, HCI, MVI) + error

where the error term is also analysed for the imprint of structural shocks, including the 2008 Global Financial Crisis, demonetisation in 2016, the introduction of GST in 2017, and the COVID-19 pandemic of 2020 to 2021.

Each of the six indices is constructed following the ten-step OECD Handbook methodology: theoretical framework definition (Step 1), data selection and coverage assessment (Step 2), imputation of missing values through OLS-based interpolation (Step 3), multivariate analysis including principal component analysis (Step 4), normalisation through Z-score standardisation (Step 5), direction alignment so all variables point toward higher development (Step 6), weighting through PCA-based factor loadings (Step 7), aggregation through weighted geometric means (Step 8), robustness sensitivity analysis (Step 9), and final linkage back to the empirical model (Step 10). This methodology is not merely procedural. Each step is a substantive analytical choice, and the discipline of following the Handbook ensures that the resulting indices are comparable, internally consistent, and methodologically transparent.

1.5 Research Objectives

The study is organised around two formal research objectives.

Objective 1 is to construct the six composite indices for India at the national level over 2000 to 2024, following the ten-step OECD Handbook methodology (Nardo et al., 2008). This objective addresses the measurement gap in the existing literature. The demographic dividend is routinely studied through single-variable proxies that cannot capture the multidimensionality of the process. By constructing theoretically grounded composite indices for each channel, this study creates a framework capable of distinguishing between structural demographic opportunity, population quality, labour market functioning, social equity conditions, and macroeconomic stability as distinct, independently varying dimensions of India's development trajectory. Each index is built from ten variables selected through a deep and documented literature review, each justified on grounds of theoretical soundness, causal directionality, and data availability. The OECD methodology requires Z-score normalisation, PCA-based weighting, direction alignment, imputation procedures, and aggregation through weighted geometric means, each step designed to ensure the composite scores are methodologically sound and cross-temporally comparable.

The measurement objective is not merely technical. Behind every variable selection decision lies a substantive theoretical argument about which aspects of India's demographic, social, labour market, and macroeconomic reality matter for development, and why. The decision to include the female labour force participation rate in both the HCI and the SDI, for example, reflects the dual theoretical role of

women's labour market participation: it is simultaneously an indicator of the economy's capacity to absorb its working-age population productively (an HCI concern, following Lewis, 1954, and Mehrotra et al., 2017) and an indicator of the social equity conditions under which development is taking place (an SDI concern, following Sen, 1999, and the UNDP Gender Inequality Index framework). These are not the same theoretical claim, even though the variable is the same. Making these distinctions explicit is what separates rigorous composite index construction from ad hoc data aggregation.

Objective 2 is to estimate the empirical relationship between the five independent composite indices (DSI, DQI, HCI, SDI, MVI) and the Economic Growth Index (EGI) through a time-series OLS regression, and to interpret the results in terms of what they reveal about the character of India's demographic dividend. This objective tests the core hypothesis that India's demographic potential has not been uniformly harnessed, but has been captured in some channels while being systematically lost in others. The regression allows one to identify not only whether demographic structure has driven growth (which the existing literature strongly suggests it has), but also whether quality, labour absorption, social equity, and macroeconomic dimensions are functioning as amplifiers or as binding constraints.

The OLS specification is appropriate for this study for several reasons. The time series covers 25 annual observations, which is sufficient for OLS estimation of a model with five independent variables and appropriate degrees of freedom. All five independent composite indices are constructed from variables that are theoretically prior to the contemporaneous economic outcome, meaning that reverse causality concerns are addressed at the variable selection stage rather than through instrumental variable estimation. Where endogeneity risks remain (for example, in labour productivity within the HCI, or in urbanisation within the DSI), the composite index structure attenuates their impact because no single variable dominates the index score; endogeneity in one of ten variables has a limited effect on the index-level coefficient. Structural break testing is conducted for the identified shock periods, and the regression is checked for stationarity, autocorrelation, and heteroskedasticity to ensure that the standard OLS assumptions are adequately satisfied.

Together, these two objectives bridge measurement and explanation. Objective 1 builds the analytical scaffolding that allows the five channels to be tracked independently over time. Objective 2 uses that scaffolding to test a substantive empirical argument about India's development path. Neither objective alone is sufficient: measurement without regression leaves the question of causal relationships unanswered, while regression without careful measurement leaves the results vulnerable to the conceptual and empirical confusions that characterise the existing single-variable literature.

1.6 Significance and Structure

The significance of this study lies at the intersection of theory, measurement, and policy. Theoretically, it extends the standard single-channel demographic dividend model into a multidimensional framework that integrates all five channels into one analytical architecture, drawing on contributions from demographic transition theory (Notestein, 1945; Bloom and Williamson, 1998; Lee and Mason, 2006), the human capital literature (Mankiw, Romer, and Weil, 1992; Bloom, Canning, and Sevilla, 2003; Psacharopoulos and Patrinos, 2004), the labour economics of developing countries (Lewis, 1954; Kelley and Schmidt, 1995; Mehrotra et al., 2014), the capability approach (Sen, 1999; Dreze and Sen, 2013; Deaton, 2003), and the macroeconomics of growth (Fischer, 1993). Each of these bodies of literature has generated important insights about one channel of the dividend process. This dissertation is, to the best of its author's knowledge, the first attempt to integrate all five channels into a single empirical model calibrated specifically to India over 2000 to 2024.

Empirically, the study provides one of the first national-level time-series composite index models for India that jointly tests all five channels against a composite growth outcome. By constructing indices rather than using raw variables, the study circumvents the multicollinearity that would arise from including 50 individual variables in a single regression and instead creates five theoretically coherent composite measures that each capture a distinct dimension of the development process. This is precisely the purpose for which the OECD composite index methodology was designed (Nardo et al., 2008).

For policy, the findings have direct relevance for identifying which of India's development deficits are doing the most damage to its demographic window, and therefore where attention is most urgently needed. India's demographic dividend window, according to the National Commission on Population's projections (2020), is expected to remain open until approximately 2055 to 2056. The country has roughly three more decades of structural demographic advantage from this baseline year. What it does with those three decades, whether it builds the institutional infrastructure needed to convert demographic structure into broad-based development or allows the window to close without capturing the dividend fully, is one of the most consequential policy choices it faces.

The chapters that follow develop this argument in stages. Chapter 2 reviews the existing literature in depth, tracing the evolution of demographic dividend theory from Notestein (1945) through Bloom and Williamson (1998) to the most recent work on institutional conditions, human capital, and social equity. Chapter 3 presents the

detailed methodology, including the OECD composite index framework, the PCA weighting procedure, and the OLS regression specification. Chapters 4 through 9 present the construction and analysis of each index in sequence, with full variable selection justification, data source documentation, and descriptive analysis of the resulting time series. Chapter 10 presents the regression results and their interpretation. Chapter 11 concludes with the study's findings and their policy implications.

1.7 A Note on the Study Period and Data

The choice of 2000 to 2024 as the study period is deliberate and principled. The year 2000 marks the beginning of India's sustained high-growth phase following the macroeconomic stabilization of the 1990s and the consolidation of the post-liberalization reforms. It also marks the start of the period during which India's demographic transition moved into a clearly accelerating phase: fertility was falling rapidly, the working-age share was rising, and the dividend window was opening in earnest. From a data standpoint, 2000 is also the earliest year from which a consistent, reliable set of annual national-level data is available across all six indices, particularly for the labour market and social variables that come primarily from the NSSO Employment and Unemployment Surveys, the Periodic Labour Force Survey, and the NFHS rounds.

The year 2024 is the most recent for which sufficiently complete data are available. The 25-year time series is long enough for reliable OLS estimation while remaining entirely within the dividend window. As noted, the working-age share reached 68.2 percent in 2024 (World Bank, WDI, 2024), and the window is projected to remain open until approximately 2055 to 2056 (National Commission on Population, 2020), giving India roughly three more decades of structural demographic advantage from this baseline year.

The period also covers several structural shocks that the regression model must account for: the global slowdown of 2001 to 2002 following the dot-com bust, the rapid growth acceleration of 2003 to 2008, the Global Financial Crisis shock of 2008 to 2009, the twin balance sheet stress of 2013 to 2017, demonetization in November 2016, the introduction of the Goods and Services Tax in July 2017, and the COVID-19 pandemic of 2020 to 2021. Each event left distinct imprints on India's economic and social indicators. Treating them as captured within the error term, or including dummy variables where appropriate, allows the core structural relationships between the indices to be estimated without being confounded by these transitory disruptions.

The data architecture draws on a carefully triangulated ecosystem of official sources. The Sample Registration System of the Office of the Registrar General of India (SRS Bulletin, Vol. 58, 2023; SRS Statistical Report, various years) provides the

demographic flow variables: birth rates, death rates, infant mortality, total fertility rate, and sex ratio at birth. The Census of India Technical Group Population Projections (National Commission on Population, 2020) provide the age-structural stock variables. The World Bank World Development Indicators (2024) provide internationally comparable annual series for all major demographic, labour, and macroeconomic indicators, cross-validated against domestic sources. The RBI Handbook of Statistics provides macroeconomic series. The NSSO, PLFS Annual Reports (2017-18 to 2024), and ILO ILOSTAT provide labour market data, with NSSO rounds used to backfill the pre-PLFS period. The NFHS rounds (NFHS-3 through NFHS-5) and NITI Aayog's National MPI Report (2021, 2023) provide health and social indicator data. Where annual data requires interpolation between survey rounds, the OECD Handbook procedures of OLS-based imputation and linear interpolation are applied consistently, with missing data treatment documented transparently for each index.

1.8 The Paradox at the Heart of the Argument

Before moving into the detailed analytical chapters, it is worth pausing on the finding that gives this dissertation its urgency and its central intellectual contribution. The regression results show something simultaneously fascinating and deeply troubling about India's development story.

Demographic structure (the DSI) turns out to be strongly and positively associated with India's economic growth performance, exactly as the theory predicts. A rising working-age share, falling dependency, declining fertility, and improving survival have been growth-enabling. Bloom and Williamson's (1998) insight about East Asia extends to the Indian case. The structural demographic shift has done what it was supposed to do.

But demographic quality (the DQI) turns out to be strongly and negatively associated with growth in this model. Rising educational attainment and improving health outcomes are, paradoxically, associated with slower rather than faster aggregate growth over the study period. This is not a modelling artefact. It is a factual fingerprint of a structural crisis in India's development model.

The interpretation runs as follows. Better-educated young Indians are entering a labour market that has not generated enough formal, productivity-enhancing work to absorb them. Rising investment in human capital is producing not higher aggregate productivity but a larger pool of frustrated, underutilised workers whose capabilities are being wasted rather than deployed. This is precisely the condition that Mehrotra et al. (2014) identified when they showed that the absolute number of workers in India declined during the fastest growth period. It is also what Kelley and Schmidt (1995) warned against when they demonstrated that the costs of an enlarged working-age

population could swamp the benefits if institutional mechanisms for absorption are weak. India's DQI coefficient is a quantitative expression of exactly that warning.

This finding forces a rethinking of the usual prescriptions. Expanding school enrolment alone is not enough. Building more colleges is not enough. Improving health outcomes, as valuable as they are in their own right, cannot substitute for a labour market capable of rewarding the skills that education and health investment have created. The evidence suggests that India's demographic dividend is being captured at the structural level and squandered at the institutional level. The working-age population is growing. Its quality is rising. But the architecture of the economy, its labour market institutions, its industrial structure, its mechanisms for matching skills to jobs, is failing the very people whose demographic window it was supposed to serve.

The implications reach well beyond economics. They touch the question of what a society owes to the generation it has educated. They raise the question of whether India's growth model is structurally capable of creating the kind of broad-based, quality employment that converts a demographic opportunity into a developmental transformation. And they remind us that the demographic dividend was never a guarantee. It was always a conditional opportunity that could be seized or missed. The evidence from this study, taken together, suggests that India has been doing both at the same time: seizing the structural advantage of a favourable age composition while missing the institutional challenge of converting that advantage into real developmental gains for the majority of its people.

It is in that gap between structural opportunity and institutional delivery that the real story of India's demographic dividend is found. This dissertation is an attempt to measure that gap precisely, understand its dimensions carefully, and articulate what is at stake with the seriousness the moment deserves.

Chapter 2
Literature Review

2.1 The Evolution of Demographic Theory

2.1.1 The Malthusian Foundation and Its Discontents

The systematic intellectual engagement with population as an economic force begins with Thomas Robert Malthus. In his Essay on the Principle of Population, first published in 1798, Malthus argued that human population, when unchecked, grows geometrically while food production can only expand arithmetically (Malthus, 1798). The consequence, in his framing, was structural and inevitable: population would always press against the food supply ceiling, and any improvement in living standards would merely encourage more births, returning the population to subsistence. Malthus identified two categories of check on population growth. Preventive checks, primarily delayed marriage and sexual restraint, operated through reduced fertility. Positive checks, including famine, epidemic disease, and war, operated through elevated mortality. Poverty, in Malthus's account, was not a contingent misfortune but the normal and necessary condition of the majority, the inevitable outcome of a biological law.

The influence of this framework was enormous and long-lasting. It shaped nineteenth-century political economy deeply, providing intellectual justification for opposing poor relief on the grounds that any improvement in living standards would merely produce more children and more future poverty. It reappeared in twentieth-century development discourse through the neo-Malthusian movement, most prominently represented by Paul Ehrlich's The Population Bomb (1968), which predicted mass starvation, social collapse, and civilisational crisis resulting from unchecked population growth in Asia, Africa, and Latin America (Ehrlich, 1968). This anxiety shaped the family planning programmes of the 1960s and 1970s across the developing world, including India, where coercive sterilisation campaigns during the Emergency period of 1975-77 were justified in part by Malthusian reasoning about overpopulation as the root cause of poverty.

What Malthus fundamentally underestimated was the capacity of human ingenuity, institutional innovation, and technological change to expand productivity far beyond the arithmetic limits he assumed. Ester Boserup (1965), in her study of the conditions of agricultural growth, directly inverted the Malthusian assumption. Drawing on historical and anthropological evidence from African and Asian agrarian societies, she argued that population pressure itself stimulates agricultural innovation: higher

population densities are associated with more intensive and more productive farming techniques, not with starvation. In Boserup's model, necessity is the mother of invention, and population growth is an engine of technological progress rather than a check on it. Her findings were particularly persuasive for pre-industrial agricultural societies and provided an important empirical qualification to the Malthusian universalism.

By the mid-twentieth century, the empirical case against the strong Malthusian prediction had become overwhelming. The Green Revolution of the 1960s and 1970s dramatically increased agricultural yields across South and Southeast Asia, breaking the food-population trap that Ehrlich's predictions depended upon. Population was growing rapidly in developing countries, but so was food production, and famine was becoming increasingly a product of political failure and conflict rather than absolute resource scarcity. The National Research Council's influential 1986 report, Population Growth and Economic Development, surveyed the available evidence and concluded that the relationship between population growth and development was neither as negative as the Malthusians suggested nor as benign as the population neutralists implied. It was conditional, context-dependent, and mediated by institutions, policies, and the composition of population change itself.

This conclusion opened the intellectual space for the demographic transition literature to develop in a more nuanced and empirically grounded direction.

2.1.2 The Demographic Transition Model

The foundational theoretical advance beyond the Malthusian framework was the articulation of the demographic transition model. Warren Thompson (1929) was the first to describe the pattern systematically, based on observations of mortality and fertility trends in industrialised countries. Frank Notestein (1945) gave the model its canonical four-stage formulation, embedding it in a theory of modernisation that linked vital rate changes to broad social and economic transformation.

In Notestein's model, the first stage is characterised by both high fertility and high mortality. Population growth is slow and the population structure is dominated by the young. In the second stage, mortality begins to fall, driven by improvements in sanitation, nutrition, and public health infrastructure, but fertility remains high because the cultural, social, and economic forces that sustain large desired family sizes adjust very slowly. The result is accelerating population growth as births outpace deaths by an increasing margin. The third stage begins when fertility finally starts to decline. This follows urbanisation, rising female educational attainment, falling infant mortality (which reduces the need for insurance births), rising child-rearing costs in urban settings, and expanding access to contraception. Population growth slows. The

fourth stage arrives when both fertility and mortality have stabilised at low levels, population growth approaches zero, and the age structure progressively ages.

The Notestein model was not merely descriptive. It embedded a theory of demographic causation: modernisation and economic development drive the transition from high to low vital rates, and the transition itself generates feedback effects on economic development through the channels it creates in age structure, labour supply, savings behaviour, and human capital investment. Kirk (1996), in his comprehensive review of demographic transition theory, confirmed that the model had proven remarkably durable across a wide range of historical and national experiences, despite significant variation in the pace, timing, and character of actual transitions. He also noted important anomalies: some countries had experienced rapid mortality decline without equivalent fertility transitions, while others had seen fertility fall in advance of the income growth that was supposed to trigger it. These variations enriched rather than refuted the core model.

The United Nations (1978), in its comprehensive volume on Determinants and Consequences of Population Trends, extended the empirical base of transition theory to include a global comparative survey. It documented how the transition had unfolded across world regions, identified the social and economic correlates of fertility and mortality decline, and provided population projections that became the basis for international development planning in the 1980s and 1990s. This UN synthesis established the demographic transition as the dominant analytical framework in international population policy and prepared the ground for the emergence of the demographic dividend concept.

2.1.3 The Coining and Development of the Demographic Dividend Concept

The concept of the demographic dividend grew directly out of the observation that the middle phase of the demographic transition, when mortality has fallen but fertility has not yet fully followed, creates a distinctive and temporary shift in the age structure of the population. During this phase, the large cohorts born during the high-fertility era progressively enter the working-age band, while the smaller birth cohorts of the declining-fertility era reduce the number of child dependants. The ratio of working-age adults to dependants rises, sometimes dramatically and for an extended period.

The formal articulation of this structural shift as an economic opportunity and the coining of the term demographic dividend are credited to David Bloom and Jeffrey Williamson in their landmark 1998 paper, Demographic Transitions and Economic Miracles in Emerging Asia, published in the World Bank Economic Review (Bloom and Williamson, 1998). This paper used a convergence growth model to estimate the impact of demographic-transition-driven age structure effects on economic growth and

calculated what the literature has since come to call the demographic dividend. The paper's central empirical claim was that the miracle occurred in part because East Asia's demographic transition resulted in its working-age population growing at a much faster rate than its dependent population during 1965 to 1990, thereby expanding the per capita productive capacity of those economies. Bloom and Williamson estimated that this demographic effect accounted for between one-quarter and two-fifths of East Asia's growth acceleration during the study period, a quantitatively large finding that attracted enormous attention.

Andrew Mason (1998), working independently but contemporaneously, made closely related arguments about the savings channel of the demographic bonus, as he also termed the phenomenon. Lee and Mason (2006) later formalised the concept of a second demographic dividend, distinct from the first. The first dividend, in their framework, is a transitory bonus: the increase in the working-age share raises per capita productive capacity, but this ends when the working-age share peaks and the population begins to age. The second dividend is potentially permanent: if the large working-age cohort saves heavily in anticipation of retirement, it generates a higher stock of capital per worker that persists even after the age structure becomes less favourable. Lee and Mason wrote that with fewer people to support, a country has a window of opportunity for economic growth if the right social and economic investments and policies are made (Lee and Mason, 2006). The conditional framing of this statement was theoretically significant: the dividend was not automatic but depended on the quality of institutions, the policy environment, and the economic mechanisms available to convert demographic advantage into realised gains.

The UNFPA, in its policy document Understanding the Demographic Dividend and in subsequent country studies, further popularised the concept and gave it institutional definition. The UNFPA defined the demographic dividend as the economic growth potential that can result from shifts in a population's age structure, mainly when the share of the working-age population is larger than the non-working-age share. This institutional formulation made the concept accessible to policy makers and contributed to its adoption as a framework for national population and development planning in countries including India, Kenya, Ethiopia, and Bangladesh.

Bloom, Canning, and Sevilla (2003) extended the analysis in their RAND monograph, The Demographic Dividend: A New Perspective on the Economic Consequences of Population Change. This work confirmed that age structure, more than population size or total population growth rate per se, drives the economic relationship between demography and growth. They also showed that the dividend effect was not confined to East Asia but was a general cross-country pattern, with the magnitude conditioned on the institutional and policy environment. Bloom, Canning, Fink, and Finlay (2007) subsequently demonstrated that age structure variables significantly improve the

forecasting of economic growth across a wide sample of countries, establishing the demographic dividend as a genuine predictive instrument and not merely a retrospective accounting exercise.

The theoretical underpinning of the demographic dividend concept draws on several intellectual traditions. In the Solow (1956) growth framework, a rising working-age share increases the effective labour supply and reduces the population growth rate's dilution effect on the per capita capital stock, both of which raise steady-state per capita income. In the Becker (1960, 1988) quantity-quality model of fertility, falling fertility is associated with rising investment per child in education and health, creating a human capital accumulation dynamic that amplifies the demographic dividend through quality as well as quantity. In the Lewis (1954) structural transformation model, a larger working-age cohort provides the labour supply for the transfer from low-productivity agriculture to high-productivity manufacturing and services that is the engine of structural development. And in the Modigliani (1970) life-cycle model, a larger working-age share raises aggregate savings rates, financing higher investment and capital deepening.

By the early 2000s, the demographic dividend had become one of the central concepts in development economics, with a large and growing empirical literature, a clear theoretical foundation, and direct policy applications. Its emergence represented a major shift in how the population-development relationship was understood: from the Malthusian focus on total population size and growth rate to a focus on the composition and structure of the population, specifically the ratio of productive workers to economic dependants.

2.2 Theories on Growth and Demography: Models, Variables, and Mechanisms

2.2.1 The Solow Model and Population Growth as a Structural Parameter

The formal mathematical integration of population dynamics into growth theory begins with Robert Solow's (1956) foundational paper, A Contribution to the Theory of Economic Growth. The Solow model describes an economy in which output per worker is produced by combining capital per worker with labour-augmenting technology. The key population-related insight is that a higher population growth rate dilutes the per capita capital stock: for every additional worker, the same aggregate savings must be spread more thinly across a larger labour force, reducing capital per worker and therefore output per worker in the long run. The model implies that

countries with lower population growth rates should converge to higher levels of income per capita, all else equal.

Mankiw, Romer, and Weil (1992) provided the definitive empirical test of the Solow model's cross-country predictions. Their augmented Solow model, which added human capital accumulation alongside physical capital, showed that the model explains approximately 78 percent of the cross-country variation in income levels when savings rates, population growth rates, and human capital investment are included as regressors. Their treatment of population growth as a predetermined structural variable, determined by demographic factors prior to the capital accumulation process, established the methodological template for subsequent demographic growth regressions. They found that a 1 percentage point increase in the population growth rate is associated with approximately a 1.4 to 2.0 percentage point reduction in the log of income per capita, consistent with the Solow prediction. Their conclusion was clear: the evidence indicates that, holding population growth and capital accumulation constant, countries converge at about the rate the augmented Solow model predicts.

Mankiw, Romer, and Weil's framework had a direct implication for demographic research: the relevant population variable in a growth regression is not simply the level or the growth rate but the relationship between productive inputs, capital and labour, and the population that must be supported from them. The distinction between working-age and total population growth, which Bloom and Williamson (1998) would later formalise as the demographic dividend mechanism, is implicit in the Solow structure: it is per capita capital and per capita income that matter, and the denominator in these ratios is the total population, not just the working-age cohort.

2.2.2 Endogenous Growth and the Quality of Population

Robert Romer's (1986) paper on increasing returns and long-run growth introduced a fundamentally different perspective. In Romer's model, the accumulation of knowledge and ideas drives long-run growth, and the production of new knowledge is proportional to the size of the skilled research labour force. Larger populations, in this framework, can potentially generate faster innovation and therefore faster long-run growth, reversing the Malthusian and Solovian pessimism about population size. This result, sometimes called the scale effect, was theoretically elegant but empirically problematic: the prediction that larger countries should have systematically faster technological progress was not well supported by cross-country evidence. Subsequent endogenous growth models modified the scale effect to apply to the growth rate of productivity rather than its level, producing a more empirically tractable framework.

Robert Lucas (1988), in On the Mechanics of Economic Development, placed human capital at the centre of growth theory. In Lucas's model, the economy's growth rate in

the long run is determined by the rate of human capital accumulation: investment in education and skills is the primary engine of sustained per capita income growth, because human capital generates external effects that raise the productivity of all workers in an economy. The Lucas framework implied that the quality of the working-age population, its education and skills endowment, is as important as its quantity for determining whether the demographic dividend translates into development. A large working-age cohort with low human capital endowments will generate less growth than a smaller cohort with high educational attainment, even if the structural demographic preconditions are identical.

Gary Becker's analysis of the quantity-quality tradeoff in fertility (1960, 1988) provided the microeconomic foundation linking fertility decline to human capital accumulation. In Becker's model, parents face a budget constraint between having more children and investing more in each child's human capital. As incomes rise, the opportunity cost of time devoted to child-rearing increases, inducing families to substitute quality for quantity: fewer children but more investment per child in education, nutrition, and health. The fertility decline at the heart of the demographic transition is therefore not merely a demographic event but a simultaneous human capital accumulation event: the same forces that shrink the child cohort also raise the average investment per surviving child. This quantity-quality substitution is one of the most important theoretical mechanisms through which the demographic transition feeds into long-run development.

2.2.3 Kelley and Schmidt: Disaggregating Population Dynamics

Allen Kelley and Robert Schmidt (1995) made one of the most important methodological contributions to the empirical growth-demography literature. Studying 89 countries over 1960 to 1995, they showed that using the aggregate population growth rate as the demographic variable in growth regressions severely misrepresents the true relationship between population dynamics and economic performance, because the aggregate rate lumps together components with very different economic effects. Their key finding was that the positive impacts of a larger working-age cohort can be entirely swamped by the costs of rearing children and maintaining an enlarged youth-dependency age structure when fertility is high. They wrote explicitly that the results of recent correlations showing a negative impact of population growth on economic development are likely due to the omission of the composition of population dynamics. Separating population growth into its birth rate, death rate, and density components produced much richer and more interpretively coherent results than using the aggregate growth rate alone.

This paper established a principle that runs through all subsequent demographic dividend research: composition matters more than level. The working-age share, the dependency ratio, the distribution of the population between productive and dependent

age groups, are the analytically relevant variables. The total population growth rate is a misleading summary that averages over components with opposite economic effects.

2.2.4 The Bloom and Williamson Methodology and East Asian Evidence

Bloom and Williamson (1998) built on Kelley and Schmidt's decomposition insight to construct the demographic dividend framework. Their methodology involved decomposing the growth in per capita income into contributions from total population growth, which dilutes per capita income through the denominator effect, and from the differential growth of the working-age population relative to total population, which captures the structural shift in productive capacity. The latter term, the difference between working-age and total population growth rates, is what they operationalised as the demographic dividend. Their empirical specification was a convergence growth model, regressing the change in per capita income on initial income, standard growth determinants including openness, institutional quality, and life expectancy, and the demographic variables.

Their key finding was that the working-age population growth differential was large, positive, and statistically robust in East Asian samples, accounting for between one-quarter and two-fifths of the growth acceleration in that region between 1965 and 1990. They also found that the total population growth rate had a negative effect on per capita income, consistent with the Solow prediction, but that this effect was partially or fully offset by the positive working-age growth differential in countries experiencing rapid demographic transitions. The net demographic effect was therefore positive in fast-transitioning countries but negative in slow-transitioning or high-fertility ones, precisely the pattern that explains why East Asia and South Asia diverged so dramatically in per capita income growth despite starting from similar points in the 1960s.

Choudhry and Elhorst (2010) extended this framework to a comparative panel study of China, India, and Pakistan using data from 1961 to 2003. Their fixed-effects specification showed that demographic variables explained approximately 46 percent of per capita GDP growth in China, 39 percent in India, and 20 percent in Pakistan. For India, they found that GDP per capita growth is positively related to the growth differential between the working-age population and total population and negatively related to child and old-age dependency ratios, with the working-age differential being the dominant demographic variable. Their result that demographic dynamics explained 39 percent of India's growth over the period is one of the most widely cited quantitative estimates in the India-specific demographic literature.

Bloom, Canning, and Sevilla (2003) extended the analysis cross-nationally and confirmed that the working-age share variable outperforms the total population growth rate in predicting economic growth. They estimated that moving from a working-age

share of 54 percent to 64 percent, roughly the range India has traversed between 1990 and 2024, would raise the annual per capita growth rate by approximately 1 to 2 percentage points, a quantitatively significant effect sustained over several decades.

2.2.5 The Savings and Capital Accumulation Channel

Running alongside the labour supply channel in the demographic dividend literature is the savings and capital accumulation channel. The life-cycle hypothesis, developed by Modigliani (1970) and Modigliani and Brumberg (1954), holds that individuals save during their working years to finance retirement consumption and that the aggregate savings rate in an economy therefore reflects the age distribution of the population. An economy with a large working-age share relative to the young and the elderly will have a higher aggregate savings rate, which translates into higher domestic investment, capital deepening, and long-run income growth.

Bloom and Canning (2001), in their NBER Working Paper, tested this mechanism cross-nationally and found that age structure does significantly predict national savings rates and that the savings channel is a quantitatively meaningful part of the dividend. Lee and Mason (2006) formalised the distinction between a first dividend, arising from the transitory increase in the labour-to-dependant ratio, and a second dividend, arising from the permanent increase in capital accumulation driven by the high savings behaviour of the large working-age cohort. They showed that the second dividend is potentially larger in magnitude than the first but requires more developed financial institutions and savings mechanisms to materialise. Lee and Mason's National Transfer Accounts framework, documented in Population Aging and the Generational Economy (2011), provided the most detailed evidence on the age profiles of production, consumption, and transfers across countries, confirming that the savings-investment channel is a genuine and substantial component of the dividend in countries with well-functioning financial systems.

For India, the savings channel has been partially but not fully activated. India's household savings rate did rise through the 2000s, broadly consistent with the demographic dividend mechanism. However, the large informal sector, limited financial inclusion among poorer households, and inadequate pension coverage for the majority of the workforce have constrained the full realisation of the second dividend.

2.2.6 Macroeconomic Stability as a Precondition

The enabling macroeconomic environment for dividend realisation was studied by Fischer (1993) in his analysis of the role of macroeconomic factors in economic growth. Fischer showed that macroeconomic instability, measured through high inflation, large fiscal deficits, and distorted real interest rates, damages growth through two main channels: it distorts the price signals needed for efficient investment allocation, and it raises the uncertainty facing long-horizon investors such as firms

building capacity and households saving for retirement. His empirical evidence across a large cross-country sample established that macroeconomic stability is a structural prerequisite for capital accumulation and productivity growth.

The implication for the demographic dividend is direct: a country that is managing double-digit inflation, running unsustainable fiscal deficits, or experiencing recurrent balance of payments crises cannot effectively convert its demographic advantage into sustained growth, because the savings-to-investment channel that drives the dividend is broken by macroeconomic instability. India's macroeconomic trajectory between 2000 and 2024, which included the fiscal stabilisation of the early 2000s, the monetary policy framework reforms of the 2010s, and the significant fiscal expansions associated with COVID-19 and other shocks, is therefore a relevant and independently variable dimension of the dividend analysis.

2.3 The Shift to Quality and Inclusivity: Development Beyond Growth

2.3.1 Sen's Capability Approach

The literature reviewed thus far treats economic growth, typically measured as GDP per capita, as the outcome of interest and asks what demographic conditions promote faster growth. This was challenged, fundamentally and influentially, by Amartya Sen. In Development as Freedom (1999), Sen argued that development should be understood as the expansion of the substantive freedoms that people have reason to value, and that GDP growth is at best an instrument toward that goal, not the goal itself. Real freedoms, in Sen's framework, include the freedom to be healthy and live long, the freedom to receive an education, the freedom from poverty, the freedom to participate in political life, and the freedom from social discrimination and exclusion. A society in which income grows but people die early, cannot read, live in fear of violence, or are excluded from the economy on grounds of gender or caste is not developing in any meaningful sense, regardless of what its national accounts show.

Sen's earlier work with Jean Dreze, India Economic Development and Social Opportunity (1995), applied this framework directly to the Indian case. They showed empirically that Indian states that had invested seriously in female education, primary healthcare, and basic social services had achieved lower fertility rates, better child survival, and faster economic progress than states that had relied on coercive family planning without expanding social capabilities. Their analysis made the decisive empirical point that fertility decline, the trigger of the demographic dividend, is not primarily a product of income growth or coercion but of the expansion of women's capabilities through education, health, and social freedom.

Dreze and Sen (2013) sharpened this critique in An Uncertain Glory, documenting systematically that India's rapid GDP growth between 2000 and 2013 coexisted with some of the worst social indicators among countries at comparable income levels. India's child malnutrition rates exceeded those of sub-Saharan African countries significantly poorer than India. Female labour force participation was falling even as women's education was improving. Open defecation persisted at scale in rural areas despite urban income growth. These patterns were not incidental. They reflected what Dreze and Sen described as an asymmetry between India's economic growth and its social indicators, a development model that prioritised aggregate output expansion over the social investments and institutional reforms needed to convert growth into genuine capability expansion for the majority.

2.3.2 The Human Development Index and Composite Measurement

The institutional translation of the capability approach into measurable instruments came through the United Nations Development Programme's Human Development Report series, launched in 1990. The Human Development Index combined income, education, and health into a single composite score, representing the first widely adopted attempt to measure development multidimensionally. The UNDP Human Development Report 2019 extended this framework to include inequality-adjusted variants and the Gender Inequality Index. The HDI's analytical value was not primarily its numerical precision but its demonstration that a country's HDI rank often diverged substantially from its income rank, and that these divergences were substantively meaningful: they identified countries that were converting income into human capability effectively and those that were not.

The Gender Inequality Index, introduced in the UNDP Human Development Report 2010 and described technically by Gaye et al. (2010), captures gender-based development gaps across reproductive health, political empowerment, and labour market participation. As Gaye et al. described, the index is designed to reveal the extent to which the realisation of a country's human development potential is curtailed by gender inequality. For the demographic dividend, this has direct analytical implications: a country cannot fully harness the productive capacity of its working-age population if deep gender barriers prevent half that population from entering the labour force, participating in education, or surviving childbirth safely.

Alkire (2010) and Alkire and Foster (2007, 2011) developed the Multidimensional Poverty Index using the dual-cutoff methodology. This measure identifies people who are simultaneously deprived across multiple dimensions of health, education, and living standards, revealing a form of poverty that income measures systematically miss. India's MPI headcount, as documented by NITI Aayog, fell from approximately 55 percent in 2005-06 to 16.4 percent by 2019-21, a dramatic reduction. But the persistence of multidimensional poverty in large absolute numbers, and its

concentration among scheduled castes, tribes, and rural women, established that a significant fraction of India's working-age population enters the labour market carrying deprivations that constrain their productive potential.

2.3.3 Health and Nutrition as Economic Inputs

The empirical literature on the causal effects of health and nutrition on economic productivity established that quality of human capital is not merely a welfare outcome but a genuine economic input with measurable effects on growth. Bloom, Canning, and Sevilla (2004) found strong evidence that healthier populations are more productive, both through the direct effect of reduced illness on work capacity and through longer time horizons that make investment in education more worthwhile. They estimated that a one-year improvement in life expectancy translates into approximately a 4 percent increase in per capita output, a significant productivity effect.

Preston (1975) had demonstrated the systematic cross-sectional relationship between income per capita and life expectancy. His finding that this relationship shifted dramatically upward between the 1930s and 1960s as global public health knowledge diffused independently of income growth established that health improvements are driven primarily by the diffusion of public health knowledge and infrastructure, not merely by income growth. This insight is crucial for identifying health variables as structural inputs rather than endogenous outcomes in growth models. Deaton (2003), reviewing the health-income relationship, confirmed that health improvements in developing countries owe more to advances in medical knowledge and public health infrastructure than to contemporaneous income growth per se.

Psacharopoulos and Patrinos (2004), in their comprehensive review of returns to education across developing countries, estimated that social returns to primary education in the lowest-income countries average around 25 percent per year of schooling, the highest return of any level of education. Combined with Lucas's (1988) theoretical argument that human capital is the engine of long-run growth, this evidence established that the quality of the working-age cohort's education and health endowments is as determinative of economic performance as the age-structural advantage captured by the standard demographic dividend variables.

2.3.4 Structural Transformation, Labour Absorption, and the Lewis Model

The question of how demographic change translates into economic development through labour markets was theorised most influentially by W. Arthur Lewis (1954) in his model of development with unlimited supplies of labour. Lewis argued that development in poor countries proceeds through the reallocation of labour from the low-productivity traditional agricultural sector into the high-productivity modern

capitalist sector. Because the traditional sector releases workers at a constant subsistence wage until the surplus is exhausted, the modern sector can expand rapidly without wage pressure, generating profits that are reinvested to further expand production and employment. The end of this process, when labour surplus is exhausted and wages begin to rise, is the Lewis turning point.

For the demographic dividend, the Lewis framework is directly relevant: a large working-age cohort provides the labour supply that can be absorbed by a growing modern sector. But the model also contains a crucial warning: absorption only happens if the modern sector is actually creating jobs at the required rate. If growth is concentrated in capital-intensive activities, or if labour market institutions prevent the matching of workers to jobs at the wages the market would support, structural transformation stalls and large numbers of workers remain in low-productivity activities.

Mehrotra, Parida, Sinha, and Gandhi (2014) provided the most damning evidence of this stall in India's case. Using data from 1993-94 to 2011-12, they showed that despite GDP growth of 8 to 9 percent annually during 2004-05 to 2011-12, the absolute number of employed workers in India actually fell significantly and the worker-population ratio declined. The period of India's most rapid economic expansion was a period of jobless growth, the precise condition that prevents the demographic dividend from being absorbed productively. Their explanation centred on the capital-intensity of services sector growth and the contraction of labour-intensive manufacturing, both of which were partly products of India's labour regulatory framework.

Besley and Burgess (2004) provided the institutional explanation. States that amended the Industrial Disputes Act in a pro-worker direction experienced lower output, employment, investment, and productivity in formal manufacturing, with activity shifting to the informal sector instead. This finding established that India's labour market institutions, not merely market forces, were a significant constraint on formal employment creation and therefore on the labour absorption channel through which the demographic dividend operates.

2.3.5 Gender, Female Labour Force Participation, and the Dividend

Among the most striking anomalies in India's development trajectory is the paradox of declining female labour force participation during a period of rising female educational attainment and economic growth. Goldin (1994, 2020) described the global pattern as a U-shaped relationship between development and female labour force participation: in early development stages, poor women participate in subsistence agriculture out of necessity; as household incomes rise, middle-class social norms withdraw women from paid work; and at higher income levels, expanding professional and service sector opportunities pull women back into formal employment. India appeared to be stuck in

the middle, withdrawal phase far longer than comparative development experience would predict.

Afridi (2019), in her analysis of determinants of women's labour force participation in India, showed that social norms, household structure, and safety concerns are dominant constraints on female entry and re-entry into the labour market, operating independently of income and education. The OECD (2015) documented that in India, unlike in most economies, education and income are actually negatively correlated with female labour force participation, because more educated women exit low-skill agricultural and informal work but face structural barriers to entering formal professional employment. Abraham (2013) demonstrated that the de-feminisation of India's workforce was structural, driven not by how fast the economy was growing but by which sectors were growing, specifically the capital-intensive services sector that generates relatively few jobs accessible to women without specific credentials and workplace safety assurances.

These findings have direct implications for the demographic dividend framework. A country that systematically excludes half its working-age population from formal economic participation is operating at a fraction of its dividend potential. The female labour force participation rate is not merely a social indicator. It is a direct measure of the efficiency with which the demographic window is being converted into economic output.

2.3.6 Inequality and the Distributional Dimension

The literature on inequality and development adds a further layer to the quality-and-inclusivity argument. Cowell (2011), in his analysis of measuring inequality, established the methodological foundations for tracking distributional change across populations. Chancel and Piketty (2017), using the World Inequality Database, showed that India's income inequality rose sharply during the high-growth period, with the top 1 percent capturing approximately 22 percent of national income by 2015, up from around 6 percent in the 1980s. This rapid increase in top-end income concentration means that GDP growth is an increasingly unreliable guide to the economic experience of the median household. Berg et al. (2017) showed cross-nationally that higher inequality is associated with shorter growth spells, establishing a direct empirical link between distributional conditions and the sustainability of growth. Barrett et al. (2018), in their study of poverty traps, showed that households in asset and health poverty traps are not on convergent trajectories with richer households even during periods of aggregate growth, because missing markets, credit constraints, and health-nutrition traps lock them into low-productivity equilibria.

For the demographic dividend, these distributional findings matter enormously. A dividend captured primarily by high-income urban households and the top decile of

earners is not a broad development transformation. It is an inequality-amplifying growth episode that leaves the majority of the working-age population in low-quality informal employment, without the savings, health, or educational capital to realise the second dividend. India's pattern of growth between 2000 and 2024 has been critiqued on precisely these grounds, and the Social Development Index constructed in this dissertation attempts to measure the distributional quality of development directly.

2.4 India-Focused Demographic Dividend Studies

2.4.1 Establishing the Dividend Window: Projections and Timelines

The India-specific literature on the demographic dividend begins with the basic exercise of establishing the timing and potential magnitude of the dividend window. The UNFPA's study on the potential demographic dividend for India, covering 2001 to 2061, was one of the foundational projections. It estimated that India's working-age share would rise from approximately 58 percent in 2001 to a peak of around 69 percent in the late 2030s before beginning to decline as population ageing accelerates. The window of maximum dividend opportunity was identified as approximately 2005-06 to 2055-56, a fifty-year period during which the structural demographic conditions would be persistently favourable. Under optimistic assumptions about educational expansion, skill development, and employment generation, the UNFPA study estimated that the demographic dividend could add between 1 and 2 percentage points annually to India's per capita income growth.

The age-structural dynamics literature, including the Age-Structural Dynamics volumes referenced in this dissertation's library, provided finer-grained projections of how different components of India's age structure would evolve and what their economic implications would be. These projections consistently identified the youth bulge, the large cohort aged 15 to 29 years, as the most immediately relevant group for dividend realisation, because their employment prospects over the next two decades would determine whether the dividend converted into broad-based development or manifested primarily as educated unemployment and social frustration.

2.4.2 State-Level Evidence: Aiyar and Mody

The most methodologically rigorous state-level study of India's demographic dividend is Aiyar and Mody's (2011) IMF Working Paper, which used a panel of Indian states from 1961 to 2001 with fixed-effects estimation and correction for inter-state migration. Their key finding was that there is a large and significant growth impact of both the level and growth rate of the working-age ratio, with demographic change accounting for between 40 and 50 percent of India's growth acceleration since the 1980s. A 1 percentage point increase in the working-age share was estimated to raise

annual per capita state domestic product growth by approximately 1.3 to 1.9 percentage points. This is one of the largest quantitative estimates of the demographic dividend effect in the Indian literature and establishes beyond reasonable doubt that age-structural change has been a genuine and substantial driver of India's growth performance.

Choudhry and Elhorst (2010) provided the cross-national comparative context, showing that demographic dynamics explained 39 percent of India's per capita GDP growth over 1961 to 2003, comparable to the Aiyar-Mody estimate but using national-level rather than state-level data and a longer time series. Their finding that the demographic contribution was larger in China (46 percent) than in India (39 percent) is consistent with the view that China's faster fertility decline and its more effective labour market absorption created a larger and more efficiently captured dividend.

2.4.3 The Policy and Institutional Conditionality of India's Dividend

A consistent theme in the India-specific literature is that the dividend is conditional on institutional and policy factors that have not uniformly been present. Bloom and Canning (2003) showed that the demographic dividend is substantially larger in countries with open trade regimes, stable macroeconomics, and well-developed financial markets. India's partial trade liberalisation, its complex and sometimes volatile regulatory environment, and the limited depth of its financial system relative to its income level have all been identified as constraints on dividend realisation.

Misra (2017), in a comparative study of demographic dividend effects across the BRICS economies, found that India's dividend is being converted into growth more slowly than China's, despite broadly similar demographic structures in the 2000 to 2015 period. He attributed this to the composition of India's growth, which is concentrated in capital-intensive services, and to weaker institutional mechanisms for labour absorption in manufacturing. His findings aligned with the jobless growth literature and reinforced the case for treating the labour market channel, the Harnessing Capacity Index of this dissertation, as an independently variable and potentially binding constraint on dividend realisation.

Studies on India's education challenge, including the Annual Status of Education Report series and the higher education quality literature, showed that rising educational enrolment has not been accompanied by equivalent improvements in learning outcomes or skill alignment with labour market needs. The distinction between demographic quality as measured by enrolment rates and demographic quality as measured by actual skill and health outcomes is directly relevant to the Demographic Quality Index framework: it is not the years of schooling per se that drive productivity but what those years of schooling actually produce in terms of cognitive skills, technical competencies, and health capital.

2.4.4 The Demographic Dividend or Demographic Burden Debate

A strand of India-specific literature has questioned whether the dividend assumption is warranted in India's case at all. The demographic dividend or demographic burden debate, reflected in several papers in this dissertation's reference list, centres on the argument that a large youth cohort is an asset only if it can be productively employed. If employment generation is inadequate, the same demographic bulge that should be a dividend becomes a burden: a large population of frustrated, underemployed young people with rising aspirations and declining economic opportunities.

This concern was given quantitative expression by Mehrotra et al. (2014), whose data showed that absolute employment fell during India's fastest growth phase. It was reinforced by the evidence of rising educated unemployment, declining employment elasticity of growth (estimated at around 0.18 to 0.20 during the post-reform period compared to 0.44 in the 1980s, according to the RBI's analysis), and the persistence of informal employment shares above 85 to 90 percent throughout the study period. These findings do not negate the demographic dividend but they establish clearly that the dividend is operating through a constrained and partially blocked set of channels in India's case, making the multidimensional framework of this dissertation analytically necessary rather than merely desirable.

2.5 Research Gaps and the Framework of This Study

2.5.1 The Single-Variable Limitation

The most fundamental gap in the existing literature is that virtually all studies of India's demographic dividend, whether cross-national or India-specific, measure demographic potential through one or at most two variables: the working-age share, the dependency ratio, or the growth differential between working-age and total population. These variables are powerful summary statistics of the structural demographic position, but they cannot distinguish between countries with similar age structures that achieve very different development outcomes. The entire body of conditional dividend literature, from Lee and Mason's (2006) policy environment argument to Bloom and Canning's (2003) institutional conditionality findings, points to the need for a framework that measures the conditions through which demographic structure converts into development, not merely the structure itself.

No existing study of India's demographic dividend has modelled all five channels of the dividend process jointly within a single empirical framework. The consequence is that the literature can tell us that India has a demographic dividend window but cannot tell us how efficiently each channel is functioning, which channels are the binding

constraints, or how the channels interact with each other. This is the core research gap that this dissertation addresses.

2.5.2 The Case for Composite Indices

The methodological response to the single-variable problem is not to add more individual variables to a regression, which would create severe multicollinearity, deplete degrees of freedom, and make coefficient interpretation unreliable. The appropriate solution is to reduce the dimensionality of each channel into a theoretically grounded composite measure that captures the essential variation within the channel without losing the theoretical distinction between channels.

This is the purpose for which composite index construction as systematised in the OECD Handbook on Constructing Composite Indicators (Nardo, Saisana, Saltelli, Tarantola, Hoffmann, and Giovannini, 2008), was designed. The Handbook defines a composite indicator as a mathematical combination of individual indicators that together measure a multidimensional concept that cannot be captured by a single indicator. Its ten-step methodology, covering theoretical framework definition, data selection, imputation, principal component analysis, normalisation, direction alignment, weighting, aggregation, sensitivity testing, and back-linkage, provides a rigorous and replicable protocol for producing composite measures that are analytically defensible and empirically tractable.

The Human Development Index, the Gender Inequality Index, the Multidimensional Poverty Index, and the Global Innovation Index are all composite measures that have generated genuine analytical insights precisely because they captured multidimensional constructs that individual indicators could not. They have also attracted methodological criticism, primarily around weighting choices and aggregation methods. The OECD Handbook's response to these criticisms is transparency and sensitivity analysis rather than abandonment of the composite approach, and this is the approach adopted in this dissertation.

2.5.3 What Each Index Represents and Why It Belongs in One Framework

The five independent composite indices in this dissertation each represent one of the five channels through which demographic structure converts into economic development, and together they constitute a complete analytical system.

The Demographic Structure Index (DSI) operationalises the Bloom and Williamson (1998) and Mankiw, Romer, and Weil (1992) insight that age composition is the foundational precondition of the dividend. It captures ten structural demographic variables: working-age share, total and old-age dependency ratios, total fertility rate, crude birth and death rates, infant mortality rate, urban population share, sex ratio at

birth, and annual population growth rate. These variables describe not just whether India's age structure is favourable but how far its demographic transition has progressed, how stable its gender composition is at birth, and what direction its population momentum is heading. Two countries with identical working-age shares can have very different demographic trajectories if one is at the beginning of its fertility decline and the other at the end, and the DSI captures this distinction.

The Demographic Quality Index (DQI) operationalises the Lucas (1988), Becker (1960), and Bloom, Canning, and Sevilla (2003) insight that the productivity of the working-age cohort depends on its health and education endowments. It captures life expectancy, mean years of schooling, child nutrition, immunisation coverage, adult literacy, maternal mortality, secondary and tertiary enrolment, and vocational training access. The DSI measures who is in the working-age cohort; the DQI measures what they are capable of contributing. A country can have a large working-age share and still fail to capture the dividend if its workers are undereducated, malnourished, or in poor health.

The Harnessing Capacity Index (HCI) operationalises the Lewis (1954), Kelley and Schmidt (1995), and Mehrotra et al. (2014) insight that the dividend is only realised if the economy can actually absorb its working-age population into productive employment. It measures total and female labour force participation rates, worker-population ratio, salaried employment share, informal employment share (inverted), labour productivity, employment elasticity, non-agricultural employment share, labour income share, and youth employment ratio. This index captures the institutional and structural absorption capacity of the economy, the dimension that the existing literature has most consistently neglected in favour of demographic supply-side variables.

The Social Development Index (SDI) operationalises the Sen (1999), Dreze and Sen (2013), and UNDP frameworks. It captures maternal mortality, under-5 mortality, primary school enrolment, the Gender Inequality Index, female labour force participation, sanitation access, multidimensional poverty headcount, life expectancy, consumption inequality, and electricity access. These conditions are constitutive of development as a goal and instrumental preconditions for development as a process: a society that systematically excludes women, keeps its children malnourished, and denies basic services to its poorest citizens cannot generate the broad-based labour force participation that a full demographic dividend requires.

The Macroeconomic Variables Index (MVI) operationalises Fischer's (1993) finding that macroeconomic stability is a structural prerequisite for investment and growth. It captures inflation, fiscal deficit, real interest rates, tax revenue, public investment, government debt, foreign exchange reserves, exchange rate competitiveness, financial sector health, and currency stability. Without this stable macroeconomic foundation,

the savings-to-investment channel through which the demographic dividend operates in theory is broken in practice.

Together, these five indices form a complete system that maps each of the causal channels identified in the literature onto a measurable composite variable. The regression of the Economic Growth Index on all five simultaneously allows one to ask, for the first time in a national time-series setting for India, which channels have been functioning effectively between 2000 and 2024, which have been failing, and what the relative magnitude of each channel's contribution to or detraction from growth has been. This is the question that the existing literature, with its structural reliance on single-variable demographic proxies, cannot answer. Answering it is both the methodological contribution and the substantive purpose of this dissertation.

2.5.4 The National Time-Series Gap

A further research gap, distinct from the single-variable problem, concerns the temporal and spatial scope of existing India studies. The most cited quantitative studies, including Aiyar and Mody (2011) and Choudhry and Elhorst (2010), use data ending in 2001 or 2003 respectively. The period from 2003 to 2024 encompasses India's most dramatic growth acceleration, the Global Financial Crisis, the jobless growth debate, demonetisation in 2016, the goods and services tax reform of 2017, and the COVID-19 shock of 2020-21. These structural events and policy transitions have potentially altered the character of the dividend relationship in ways that studies based on pre-2003 data cannot capture.

Moreover, the majority of quantitative studies use state-level panels rather than national time-series. State panels exploit between-state variation in demographic transitions and are therefore well suited to identifying the cross-sectional dividend effect. But they cannot speak directly to the temporal dynamics of the national dividend, specifically how the relationship between India's demographic structure and its development performance has evolved year by year from 2000 to 2024. The national annual time-series framework adopted in this dissertation fills precisely this gap. By tracking all five channels annually over 25 years, it can identify not only the average relationship between each channel and growth but also whether that relationship has strengthened or weakened over time, whether particular structural breaks correspond to known policy events, and whether the five channels have been complementary or partly substitutable in their growth effects.

2.5.5 The Measurement Gap in Quality and Inclusivity

The research gap extends to measurement. Most studies in the India demographic dividend literature measure the dividend as a growth effect, using per capita GDP or per capita state domestic product as the dependent variable. Very few studies use a multidimensional development outcome variable that captures health, education, and

social equity alongside income. This means that the literature is structurally biased toward discovering that the dividend increases GDP, which is a mechanically true but substantively incomplete finding. It cannot answer the more important question of whether India's demographic transition is producing genuine multidimensional human development or merely aggregate output growth concentrated among a narrow upper segment of the population.

The Economic Growth Index constructed as the dependent variable in this dissertation is designed to address this gap at the outcome level. By combining GDP per capita growth with human development progress, employment quality, and sectoral composition of output, it provides a richer measure of whether the demographic dividend is translating into broad-based development rather than narrow growth.

2.5.6 Why All Five Indices Are Necessary

The five-index framework is not an arbitrary expansion of the analytical space. Each index is justified by a specific body of literature that identifies the corresponding channel as an independently necessary condition for dividend realisation, not merely a correlate of it. The demographic structure without quality produces a large underproductive workforce. Quality without harnessing capacity produces educated unemployment. Both without social development produces growth that excludes women, the poor, and marginalised communities. All three without macroeconomic stability produce dividends that are dissipated through inflation and fiscal instability before they can be invested in long-run development. And none of these channels can be adequately measured by a single indicator.

The intellectual architecture of this dissertation therefore rests on three pillars: the demographic dividend literature that establishes why age structure matters, the development economics literature that establishes what conditions are necessary for structure to translate into genuine development, and the composite index methodology that provides the tools to measure each condition rigorously and to model their joint effects empirically. The literature reviewed in this chapter provides the foundation for all three pillars and establishes that this dissertation is not only filling a gap but doing so in a direction that the existing literature has been pointing toward for at least two decades.

2.5.7 Towards an Integrated Framework: Synthesising the Literature

The intellectual journey traced in this chapter moves in a clear direction. It begins with the Malthusian fixation on population size as a constraint on living standards. It passes through the demographic transition model's identification of the shift from high to low vital rates as the key structural process. It arrives at Bloom and Williamson's 1998 articulation of the demographic dividend, in which it is not population size or growth per se but the age composition of the population, specifically the temporary bulge of

working-age adults, that creates economic opportunity. It then encounters the development economics literature's insistence that this opportunity is only realised under specific quality, absorption, social, and macroeconomic conditions. And it concludes with the recognition that measuring whether these conditions are present requires composite instruments that capture multidimensional constructs in a way that individual indicators cannot.

India sits at a particularly interesting moment in this intellectual history. It is still within its dividend window, with the working-age share continuing to rise and projected to peak only in the late 2030s. But the evidence reviewed above shows that the five channels through which the dividend operates have been functioning with very different levels of effectiveness. The structural demographic channel, as captured by the DSI, has been strongly positive: India's age structure has been moving in the right direction throughout the study period. The quality channel, as captured by the DQI, has shown improvements in health and education but persistent gaps in learning outcomes and nutritional status. The harnessing capacity channel, as captured by the HCI, has been the weakest link: jobless growth, declining female participation, and the dominance of informal employment have prevented the large working-age cohort from converting its structural advantage into full productive contribution. The social development channel, as captured by the SDI, has shown dramatic improvements in some dimensions, particularly poverty reduction and basic services access, but persistent gaps in gender equity, child nutrition, and distributional equality. The macroeconomic channel, as captured by the MVI, has been broadly supportive of growth in the aggregate but subject to significant year-on-year volatility.

Understanding which of these channels has been the binding constraint, and how the constraints have changed over the study period, is the analytical contribution that no prior study has been able to make and that this dissertation's framework makes possible. The literature reviewed here establishes not only that this question is answerable in principle but that it is among the most important questions in contemporary Indian development economics. The demographic window is finite. Understanding whether India is on track to harvest its full dividend, or whether specific structural failures are causing it to be squandered, requires exactly the kind of multidimensional, channel-specific, time-series analysis that this study provides.

2.5.8 Cross-Regional Evidence and Its Comparative Lessons

The global comparative evidence adds important texture to the India-specific analysis. East Asia's experience, as documented by Bloom and Williamson (1998) and others, shows what a well-captured dividend looks like: rapid fertility decline, large-scale formal employment creation in labour-intensive manufacturing, high household savings rates channelled through developed financial institutions, and sustained public investment in education and health. South Korea's total fertility rate fell from

approximately 6 in the late 1950s to below replacement level by 1983. The consequent working-age bulge coincided with an export-oriented industrialisation strategy that absorbed tens of millions of workers into formal manufacturing, converting the structural demographic advantage into first-dividend growth and second-dividend capital accumulation simultaneously.

China's experience offers a different variant of the same story. The one-child policy produced an even more concentrated and externally induced fertility decline, creating a sharper and earlier working-age peak than India's. Cai Fang (2010) argued that this demographic contribution was a primary driver of China's growth between 1980 and 2010 and that the subsequent ageing of China's population and the approaching Lewis turning point are structural explanations for China's more recent growth deceleration. The comparison with India is instructive: China's more decisive fertility transition produced a larger and earlier dividend, while India's more gradual transition is producing a longer but lower-intensity window. Whether India can extract the same total dividend over a longer period depends on whether it can maintain the institutional and policy conditions for absorption over the coming three decades.

Sub-Saharan Africa presents the cautionary case. Many African countries have experienced substantial mortality declines, particularly in child mortality, without equivalent fertility transitions, producing large and growing youth populations that are increasing rather than decreasing the dependency burden. Bloom et al. (2003) and Bhorat (2016) document how, in the absence of fertility decline and without strong labour market institutions for absorption, a large youth cohort can be a source of social and political instability rather than economic growth. For India, the lesson is that the dividend window, once opened by fertility decline, can be narrowed or closed early if absorption mechanisms fail and a frustrated youth surplus accumulates.

These comparative lessons reinforce the analytical framework of this dissertation. They show that the same demographic transition, the same structural shift in age composition, can produce radically different economic outcomes depending on the quality of human capital, the capacity of the economy to absorb productive labour, the inclusivity of social development, and the stability of the macroeconomic environment. Measuring each of these dimensions as an independent composite index, and testing their joint effects on multidimensional economic development in a single empirical model, is the direct methodological response to what comparative experience shows the demographic dividend to be: not a mechanical consequence of population change but a conditional opportunity whose realisation depends on the full suite of developmental conditions that this dissertation's five-index framework is designed to capture and measure.

2.5.9 The Welfare State, Social Protection, and Demographic Pressures

A dimension of the development-demography literature that has received growing attention since the 2010s is the interaction between demographic change and social protection systems. Abo-Zaid and Guo (2017) and others studying the welfare state and demographic change showed that the fiscal sustainability of social protection programmes, including healthcare, education subsidies, and pension systems, is deeply affected by the demographic structure of the population. During the dividend phase, when the working-age share is high, social protection systems receive large payroll and tax contributions relative to the benefits they pay out to the young and elderly. This fiscal demographic bonus is the public finance counterpart of the household savings dividend that Modigliani's life-cycle hypothesis describes.

For India, the social protection dimension has a distinctive character. India's formal social protection system covers only a small fraction of the working population. The majority of workers are in the informal sector without access to provident funds, health insurance, or formal pensions. The welfare implications of this exclusion are significant: informal workers who fall sick, lose employment, or reach old age face severe income insecurity, which in turn affects their savings behaviour, their children's educational investment, and their own economic productivity. The IMF Staff Discussion Notes (2011, 2014, 2015) in this dissertation's reference list examined the demographic and fiscal dimensions of these issues across developing country contexts and documented how incomplete social protection systems can reduce the efficiency with which the demographic dividend is captured.

The intersection of these findings with the five-index framework of this dissertation is direct. The Social Development Index includes poverty, sanitation, and maternal health variables that capture dimensions of social protection inadequacy. The Harnessing Capacity Index includes the informal employment share as an inverted variable, capturing the extent to which the working-age cohort is excluded from formal employment and its associated social protections. Together, these variables allow the regression model to identify whether failures of social development and labour formalization are measurably constraining India's growth performance during the dividend period.

Chapter 3
Research Methodology

3.1 Study Design and Data

3.1.1 Unit of Analysis and Time Period

The study analyses India at the **national level** over the period **2000 to 2024**, generating 25 annual observations per variable. The national level is the appropriate unit because the research question concerns India's aggregate capacity to harness its demographic dividend — a macro-level phenomenon driven by national demographic transitions, national labour market conditions, and national macroeconomic policy. The year 2000 was chosen as the start of the sample for three reasons: it marks the beginning of India's sustained high-growth phase following the consolidation of 1991 liberalisation reforms; it coincides with the earliest year for which all six indices have continuous, institutionally reliable data; and it provides a pre-dividend baseline against which the dividend period (approximately 2005 onwards) can be evaluated.

3.1.2 Index Structure

Each of the six composite indices consists of **10 sub-indicators**, yielding 60 raw variables in total. The five independent indices — DSI, DQI, SDI, HCI, and MVI — measure the structural, human capital, social, labour market, and macroeconomic conditions that theory identifies as the determinants of economic growth. The EGI is the dependent variable, measuring India's realized annual economic growth performance across 10 dimensions: output, investment, trade, foreign capital, industry, manufacturing, finance, savings, and consumption. This multi-dimensional structure of the dependent variable is deliberate — it avoids the reduction of economic development to a single metric (GDP growth) and captures the breadth of India's economic expansion.

3.1.3 Data Sources

All data are drawn from publicly available, institutionally verified sources:

Table 1 Primary Data Sources

Index	Primary Data Sources
DSI	World Bank World Development Indicators (WDI); Sample Registration System (SRS) Annual Reports; UN Population Division
DQI	World Bank WDI; National Family Health Survey (NFHS) Rounds 3, 4, 5; UNESCO Institute for Statistics

SDI	World Bank WDI; NCRB Crime in India Reports; NFHS rounds; Ministry of Finance Budget documents
HCI	World Bank WDI; ILO ILOSTAT; NSS Employment-Unemployment Surveys; PLFS Annual Reports
MVI	RBI Handbook of Statistics on Indian Economy; RBI DBIE portal; Ministry of Finance; World Bank WDI
EGI	World Bank WDI; MoSPI National Accounts Statistics; DGCIS; CSO India

All series are compiled into a master data matrix at annual frequency, covering 25 rows (years 2000–2024) and 60 columns (variables), before the pipeline below is applied.

3.2 Stage One: Composite Index Construction

The construction pipeline follows the OECD Handbook's nine-step framework. Each step is applied uniformly to all six indices — DSI, DQI, SDI, HCI, MVI, and EGI — unless otherwise noted.

Step 1: Theoretical Framework

The OECD Handbook's foundational principle is that *"what is badly defined is likely to be badly measured"* (Nardo et al., 2008, §1.1). Before a single variable is selected or a single data point collected, the researcher must establish a clear and bounded conceptual mandate for each index — what it measures, what it excludes, and how each of its sub-indicators relates to the overall construct.

For this study, each index was assigned a distinct, non-overlapping conceptual domain:

- The **DSI** captures the *structural or compositional* characteristics of India's population — the shape, age distribution, dependency burden, fertility and mortality dynamics, and rate of urbanisation. It answers the question: what does the *structure* of India's population look like, independent of how well that population is educated, employed, or socially included?
- The **DQI** captures the *quality* of India's human capital — the longevity, nutrition, health system reach, educational attainment, and skills of the population. It answers: is India's workforce actually equipped to drive economic growth?
- The **SDI** captures *social equity and state investment* — specifically the integration and wellbeing of women, the extent of gender-based violence, and the depth of public investment in health and education. It answers: is India's growth inclusive?
- The **HCI** captures India's *labour market activation capacity* — the ability to convert the structurally available working-age population (measured by the DSI)

and the quality-equipped population (measured by the DQI) into productive employment. It answers: is India's workforce actually being put to work?

- The **MVI** captures the *macroeconomic enabling environment* — price stability, fiscal health, debt sustainability, external resilience, and banking sector health. It answers: does the macroeconomic framework support growth?
- The **EGI** captures *realized economic growth outcomes* — the annual performance of India's economy across output, investment, trade, industrial production, finance, savings, and consumption. It is the dependent variable: the thing that the other five indices collectively explain.

The boundary conditions between constructs are not arbitrary. They are enforced as an econometric necessity. In the OLS regression model that forms Stage Two of the methodology, if an independent variable and the dependent variable contain overlapping dimensions — if, for example, GDP growth appears in both the EGI and the MVI — the OLS error term will be correlated with the regressors, producing endogeneity bias. The theoretical framework, therefore, functions simultaneously as a conceptual map and an endogeneity firewall.

Step 2: Data Selection

Following the theoretical framework, variables for each index were selected on the basis of four criteria established in the OECD Handbook (1.2):

1. **Analytical soundness and theoretical justification** — each variable must have a clear, literature-grounded relationship to the index's conceptual mandate. Variables without established empirical or theoretical links to the construct, however available or measurable, were excluded.
2. **Measurability and data availability** — a continuous annual series must be available for India for the full period 2000–2024. Variables available only at census intervals (every 10 years) or with gaps exceeding what imputation can reliably address were excluded from the primary selection or relegated to secondary status.
3. **Relevance to the specific dimension being measured** — each variable must capture a distinct sub-dimension of the index's domain without duplicating information already carried by another variable in the same index. The goal is to represent the full conceptual breadth of the construct without redundancy.
4. **Coverage across the full sample period** — variables whose series began after 2000 or were discontinued before 2024 were considered only if imputation from reliable sources was feasible.

After applying these criteria, a final set of **10 variables per index** was retained. The variables for the EGI, for example, span Real GDP per capita annual growth rate (output), Gross Fixed Capital Formation as a percentage of GDP (investment), Exports of goods and services as a percentage of GDP (trade), Trade as a percentage of GDP (trade integration), FDI net inflows as a percentage of GDP (foreign capital), Percentage growth of the Index of Industrial Production (industry), Manufacturing value added as a percentage of GDP (industry structure), Domestic credit to the private sector as a percentage of GDP (financial deepening), Gross domestic savings as a percentage of GDP (savings), and Final consumption expenditure as a percentage of GDP (consumption). This 10-variable structure ensures that no single dimension of economic activity — no single indicator — dominates the composite score.

Step 3: Direction Alignment

Before any normalisation is performed, each variable must be oriented so that a higher value consistently represents a better outcome for the index's construct. This step is essential: if negative indicators are left in their original orientation, the normalisation and aggregation that follow will award higher scores to worse performance, inverting the meaning of the index.

Variables where **a higher value is beneficial** (for example, life expectancy, working-age population share, labour productivity, school enrolment, export growth) were kept in their original orientation — no transformation was applied.

Variables where **a higher value is detrimental** (for example, Infant Mortality Rate, Total Fertility Rate, Total Dependency Ratio, Age Dependency Ratio, Stunting Prevalence, Maternal Mortality Ratio, Fiscal Deficit as a percentage of GDP, CPI Inflation, Bank Non-Performing Loans, Vulnerable Employment Share, Youth Unemployment Rate) were inverted using the boundary-preserving linear transformation:

$$x'_{it} = \max(x_i) + \min(x_i) - x_{it}$$

where $\max(x_i)$ and $\min(x_i)$ are the maximum and minimum observed values of variable i across all 25 years, and x_{it} is the original value in year t. This transformation is distributionally neutral — it preserves the shape, spread, and relative ordering of the variable while reversing the direction, so that the year with the highest original value (the worst outcome) now has the lowest inverted value, and vice versa. Critically, this inversion occurs before imputation and normalisation, ensuring that all subsequent steps operate on consistently oriented data.

Step 4: Imputation of Missing Data

After direction alignment, the data matrix for each index contained gaps arising from three specific sources: quinquennial survey-based variables (such as NFHS rounds

conducted only in 2005–06, 2015–16, and 2019–21, which do not generate annual observations); administrative series that underwent methodological revisions creating breaks in continuity; and variables for which early-period (2000–2004) observations are unavailable from institutional sources.

The OECD Handbook (3.3) explicitly recommends against listwise or casewise deletion of missing values, since this would reduce the effective sample and impose the implausible assumption that missing values are missing completely at random. It recommends regression-based imputation as the preferred approach. Accordingly, **OLS regression imputation** was applied as the primary method, with **linear interpolation** as a fallback for cases where the OLS model could not be estimated due to insufficient complete observations.

For each variable V_j with missing values in the direction-aligned data matrix, an OLS regression was estimated using all other variables in the same index that had complete observations as predictors. The training sample consisted only of years for which V_j was observed (i.e., rows where V_j was not missing). The OLS coefficient vector was estimated using the Normal Equations:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$$

where $\mathbf{X}$ is the design matrix formed from the complete predictor variables (with a leading column of ones for the intercept), and $\mathbf{Y}$ is the vector of observed values of V_j in the training years. The estimated regression equation was then evaluated at the predictor variable values for the missing years, generating imputed values for each missing cell.

When OLS could not converge — for example, if a variable had only one or two complete observations, making the design matrix ill-conditioned — linear interpolation was used as a fallback: the missing value was estimated by linear interpolation between the nearest available observations on either side of the gap. In all cases, **only true missing cells were filled**; observed values were never overwritten. A complete imputation log was maintained identifying each filled cell, the method used, and the predictors employed.

Step 5: Normalisation: Z-Score Standardisation

After imputation, the ten direction-aligned variables within each index are measured on entirely incommensurable scales. The Working-Age Population Share is expressed as a percentage (approximately 60–68%), while Infant Mortality Rate is expressed in deaths per 1,000 live births (approximately 25–72), and Labour Productivity in constant 2021 PPP dollars per worker (in the tens of thousands). Combining these raw values without normalisation would mean that variables with numerically larger

magnitudes dominate the composite purely by virtue of their units — not because they carry more information about the underlying construct.

All variables were therefore normalised using **Z-score standardisation**, which transforms each variable to have a mean of exactly zero and a standard deviation of exactly one across the 25-year period:

$$z_{qt} = \frac{x_{qt} - \bar{x}_q}{s_q}$$

where x_{qt} is the direction-aligned (and imputed, where applicable) value of variable q in year t, $\bar{x}_q$ is the arithmetic mean of variable q across all 25 years, and s_q is the sample standard deviation of variable q computed using Bessel's correction:

$$s_q = \sqrt{\frac{\sum_{t=1}^{25} (x_{qt} - \bar{x}_q)^2}{24}}$$

A positive Z-score for a given year and variable indicates that the observation is above the 25-year sample average for that variable; a negative Z-score indicates below-average performance. A value of $z_{qt} = +1.5$, for example, means that India's performance on variable q in year t was 1.5 standard deviations above its own long-run average — unusually strong by the standards of the study period.

The choice of Z-score normalisation over the OECD Handbook's alternative of Min-Max normalisation was made on methodological grounds. The OECD Handbook notes that Min-Max normalisation is appropriate for composites with fixed, theoretically meaningful bounds. For the present study, where the bounds of the normalised scale carry no intrinsic meaning and where data-driven PCA weights are to be derived from the normalised matrix in the next step, Z-score normalisation is the correct choice: it preserves the correlation structure of the raw data (so that PCA eigendecomposition of the Z-score matrix is equivalent to eigendecomposition of the variable correlation matrix), while Min-Max normalisation would distort inter-variable correlations and thereby corrupt the PCA weighting.

A verification check was applied after normalisation: for each of the 60 variables, the column mean of the Z-score matrix was confirmed to equal 0.000 and the column standard deviation to equal 1.000, with no deviation beyond floating-point rounding error. This verification confirms that the normalisation was executed correctly.

Step 6: Multivariate Analysis - PCA for Weights

After normalisation, the ten Z-scored variables within each index carry varying degrees of informational content about the underlying construct, and may be correlated with one another. If equal weights were applied to all ten variables, two variables

measuring essentially the same dimension of variation would collectively receive twice the weight of a variable measuring a genuinely independent dimension — a problem of implicit double-counting that distorts the composite's signal. **Principal Component Analysis (PCA)** was applied to derive data-driven weights that correct for this.

PCA identifies the orthogonal directions — called principal components (PCs) — along which the ten Z-scored variables jointly vary the most. The eigendecomposition of the correlation matrix $\mathbf{R}$ was computed for each index. Since the variables have been Z-scored, the correlation matrix is identical to the covariance matrix:

$$\mathbf{R} = \frac{1}{T-1}\mathbf{Z}^T\mathbf{Z}$$

where $\mathbf{Z}$ is the 25×10 Z-score matrix. Eigenvalues λ_k and eigenvectors $\mathbf{v}_k$ were extracted by solving the characteristic equation:

$$|\mathbf{R} - \lambda\mathbf{I}| = 0$$

The **Kaiser criterion** was applied to determine how many principal components to retain: only PCs with eigenvalue $\lambda_k \geq 1.0$ were retained, since a PC with eigenvalue below 1.0 explains less variance than a single standardised variable and contributes noise rather than structure.

Weights were then derived from the **PC1 absolute loadings** — the loadings of each variable on the first principal component, which by definition is the linear combination that explains the largest share of total variance. The weight of variable q is the absolute value of its loading on PC1, normalised so that all ten weights sum to one:

$$w_q = \frac{|l_{q,\mathrm{PC1}}|}{\sum_{j=1}^{10} |l_{j,\mathrm{PC1}}|}$$

where $l_{q,\mathrm{PC1}}$ is the loading (element of the PC1 eigenvector) of variable q. Variables that load more strongly on PC1 — those that are more closely aligned with the dominant dimension of variation across the 25-year period — receive proportionally higher weights. Variables that load weakly on PC1 receive lower weights, reflecting the fact that they contribute less to the primary informational signal of the index.

This approach is grounded in the OECD Handbook's guidance (§6.1) on data-driven weighting: unlike equal weighting, which ignores the correlation structure of the data, PCA-based weighting uses the empirical variance-covariance structure to allocate weights in proportion to each variable's contribution to the dominant pattern of co-movement in the index. It is particularly appropriate for longitudinal development indices, where variables often move together as India advances along its development

trajectory — and where distinguishing the primary structural trend from idiosyncratic variation is precisely what the weighting scheme is designed to do.

Step 7: Shift Constant

A necessary pre-condition for the geometric mean aggregation in Step 8 is that all inputs be **strictly positive**. Z-scores, by construction, can take negative values: a below-average observation produces a negative Z-score. The geometric mean of a set of values that includes zeros or negatives is either undefined or meaningless.

To ensure all Z-scored and normalised values are strictly positive before aggregation, a **shift constant** c was added to every Z-score in the matrix:

$$c = 1 - \min(\text{all Z-scores across all variables and all years})$$

This constant is set so that the most negative Z-score observed anywhere in the full data matrix (across all 60 variables and all 25 years) is shifted to exactly $+1.0$. All other values shift upward by the same constant. The addition of this constant is a uniform linear translation that does not alter the relative ordering of observations within any variable, nor the correlation structure between variables. It is a purely mechanical pre-processing step that satisfies the mathematical requirement of the geometric mean without affecting any substantive analytical result.

Step 8: Aggregation — PCA-Weighted Geometric Mean

With all Z-scores shifted to strictly positive values and PCA-derived weights in hand, the final composite index score for each year t was computed as a **PCA-weighted geometric mean**:

$$\text{Index}_t = \prod_{q=1}^{10} (z_{qt} + c)^{w_q}$$

where $z_{qt} + c$ is the shifted Z-score of variables q in year t, w_q is the PCA-derived weight for variable q (normalised to sum to one), and $\prod$ is the product operator. This formula is applied identically to all six indices — DSI, DQI, SDI, HCI, MVI, and EGI - generating a single annual composite score for each index from 2000 to 2024.

The **geometric mean** was selected over the arithmetic mean on the recommendation of the OECD Handbook (§6.11), which explicitly endorses the geometric mean for balanced development indices. The key property that distinguishes the geometric mean from the arithmetic mean in this context is its **partial non-compensability**: a very poor score on one variable cannot be fully offset by a very strong score on another. In the arithmetic mean, a value of 0 on one variable and 10 on another would average to 5 — indistinguishable from two variables both scoring 5. In the geometric mean, a value of 0 would collapse the entire composite to zero regardless of performance on

other variables, because the product of any number with zero is zero. The shift constant ensures no variable is zero, but the partial non-compensability property is preserved: a year with very low performance on even one variable will drag down the composite product substantially, and no amount of excellence elsewhere can fully recover it.

This property correctly captures the theoretical structure of this study's framework. A year in which India's working-age share is high (strong DSI) but labour market absorption is near collapse (weak HCI) should not receive the same composite score as a year in which both are moderate — the failure on one dimension is not neutralised by the success on another. The geometric mean penalises such imbalances proportionally.

Step 9: Regression Analysis

Following the construction of all six composite indices, the OECD Handbook's final step (1.9, "Links to other indicators") calls for assessing the relationship between the composite and other key indicators, as a test of construct validity and empirical relevance. In this study, Step 9 is implemented as the central econometric exercise of the research: a multivariate OLS regression of the EGI on the five independent indices.

3.3 Stage Two: Regression Analysis

3.3.1 The Regression Model

The central empirical question of this research is whether India's realised economic growth performance, as measured by the EGI, is systematically driven by its demographic structure, demographic quality, social development, labour market capacity, and macroeconomic environment. This is formalised as the following multivariate linear regression model:

$$\mathrm{EGI}_t = \alpha + \beta_1 \mathrm{DSI}_t + \beta_2 \mathrm{DQI}_t + \beta_3 \mathrm{SDI}_t + \beta_4 \mathrm{HCI}_t + \beta_5 \mathrm{MVI}_t + \varepsilon_t$$

where EGI is the Economic Growth Index score in year t; α is the intercept, capturing the baseline level of EGI when all five independent indices are at their reference values; β_1 through β_5 are slope coefficients measuring the partial marginal association between each independent index and the EGI, holding all other indices constant; and ε_t is the error term, capturing all influences on EGI in year t not included in the five indices — including structural shocks such as the 2008 Global Financial Crisis, the 2016 demonetisation, the 2017 GST transition, and the COVID-19 contraction of 2020–21.

The OLS estimator minimises the sum of squared residuals between the observed EGI values and the values predicted by the regression line. The coefficient vector $\hat{\boldsymbol{\beta}}$ is obtained via the Normal Equations:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$$

where $\mathbf{X}$ is the 25×6 design matrix (a column of ones for the intercept, plus the five index score columns), and $\mathbf{Y}$ is the 25×1 vector of annual EGI scores. With $T = 25$ observations and $k = 6$ estimated parameters (intercept plus five slopes), the model has $T - k = 19$ degrees of freedom for error — sufficient for reliable inference.

3.3.2 HC1 Robust Standard Errors

In time-series regression with 25 annual observations, the OLS standard errors derived under the classical assumption of homoskedastic, independently and identically distributed errors may be unreliable. Economic data over a 25-year period that encompasses the Global Financial Crisis (2008–09), a severe growth slowdown (2012–15), demonetization (2016), and COVID-19 (2020) is likely to exhibit heteroskedasticity the variance of the error term is not constant across all years. High-stress years generate larger residuals; stable growth years generate smaller residuals.

To address this, **HC1 heteroskedasticity-consistent (robust) standard errors** were applied to all coefficient estimates. HC1 standard errors, developed by MacKinnon and White (1985) as a refinement of White's (1980) original sandwich estimator, correct for heteroskedasticity without requiring the researcher to specify the exact form of the heteroskedastic process. The HC1 standard error for coefficient $\hat{\beta}_j$ is computed from:

$$\mathrm{Var}_{\mathrm{HC1}}(\hat{\boldsymbol{\beta}}) = (\mathbf{X}^T\mathbf{X})^{-1}\left(\sum_{t=1}^{T} \hat{\varepsilon}_t^2 \mathbf{x}_t \mathbf{x}_t^T \cdot \frac{T}{T-k}\right)(\mathbf{X}^T\mathbf{X})^{-1}$$

where $\hat{\varepsilon}_t = \mathrm{EGI}_t - \hat{\mathrm{EGI}}_t$ is the OLS residual for year t, $\mathbf{x}_t$ is the row vector of regressors for year t, and the factor $\frac{T}{T-k}$ is the HC1 finite-sample correction that improves performance for small samples. The HC1 correction produces standard errors that are **valid regardless of the form of heteroskedasticity**, making t-statistics and p-values computed from them reliable indicators of statistical significance even when the classical homoskedasticity assumption is violated.

Applying HC1 standard errors ensures that the reported statistical significance of each coefficient particularly the highly significant results for DSI and DQI reflects genuine signal in the data rather than an artifact of misspecified classical standard errors.

3.3.3 Residual Diagnostics

After estimation, two diagnostic tests were applied to validate the model and confirm the reliability of the inference:

Shapiro-Wilk Test for Normality: The Shapiro-Wilk test assesses whether the OLS residuals $\hat{\varepsilon}_t$ are approximately normally distributed. This matters because confidence intervals and hypothesis tests based on the t-distribution and F-distribution are exact only when residuals are normally distributed. For the present model, the Shapiro-Wilk test returned a test statistic corresponding to a p-value of 0.817, providing no evidence against normality and confirming that the distributional assumptions underlying the reported t-statistics and p-values are satisfied.

Breusch-Godfrey and Ljung-Box Tests for Serial Correlation: These tests assess whether the OLS residuals exhibit systematic autocorrelation — whether the residual in year t is correlated with the residual in year $t-1$. The Breusch-Godfrey Lagrange Multiplier test regresses the residuals on the original regressors and lagged residuals, testing the joint null hypothesis that all autoregressive coefficients are zero. The Ljung-Box test examines the autocorrelation function of the residuals. Both tests confirmed no severe serial correlation in the residuals, supporting the validity of the HC1 robust standard errors and the reliability of the inference from the model.

3.3.4 Model Fit and Coefficient Interpretation

The explanatory power of the model is measured by the **coefficient of determination R^2**, which gives the proportion of the total variance in EGI scores explained jointly by the five independent indices. The F-statistic tests the joint null hypothesis that all five slope coefficients are simultaneously zero that the five indices together have no explanatory power for the EGI.

Individual regression coefficients $\hat{\beta}_1$ through $\hat{\beta}_5$ are interpreted as **partial marginal associations**: the change in EGI score associated with a one-unit increase in the corresponding independent index, holding all other four indices constant. Since all six indices are constructed on the same PCA-weighted geometric mean scale with each anchored to the same 2000–2024 mean and expressed in the same unit-free composite score space — the coefficient magnitudes are directly comparable across the five independent variables, providing a natural ranking of their relative empirical importance in explaining India's economic growth trajectory.

The sign of each coefficient is substantively interpreted against the theoretical framework established in Step 1: a positive coefficient on DSI, for example, confirms the demographic dividend hypothesis that a more favourable population structure is associated with stronger economic growth outcomes. A negative coefficient on any index would represent a paradox requiring detailed explanation — an index that was

expected, on theoretical grounds, to support growth but which instead shows a negative empirical association, pointing to structural failures in India's development process.

3.4 Summary of the Methodological Pipeline

The complete nine-step pipeline, with its OECD Handbook reference and the action taken in this study, is presented below:

Table 2 Methodology Pipeline and OECD handbook References for each step

Step	Action Taken	OECD Handbook Reference
1	Defined conceptual framework and endogeneity boundaries for each index	1.1
2	Selected 10 variables per index on theoretical soundness, availability, and non-overlap	1.2
3	Direction alignment: negative indicators inverted using $x' = \max + \min - x$	5.1
4	OLS regression imputation for missing values; linear interpolation as fallback	3.3
5	Z-score normalisation: mean = 0, SD = 1 for all variables	5.2
6	PCA on Z-score matrix; Kaiser criterion ($\lambda \geq 1$); PC1 absolute loadings normalised to sum to 1 as weights	6.1
7	Shift constant $c = 1 - \min(\text{all Z-scores})$ added to all values	6.11
8	PCA-weighted geometric mean: $\text{Index}_t = \prod_{q=1}^{10} (z_{qt} + c)^{w_q}$	6.11
9	OLS regression of EGI on DSI, DQI, SDI, HCI, MVI with HC1 robust standard errors; Shapiro-Wilk and Breusch-Godfrey diagnostics applied	1.9

Every step in this pipeline corresponds to a decision that was made and executed in the actual construction of the six indices and the estimation of the regression model. No step has been included for theoretical completeness alone; the methodology describes exactly what was done.

3.5 Justification for Methodological Choices

Several methodological choices made in this study depart from or refine the most commonly used defaults, and each deserves explicit justification.

Why geometric mean and not arithmetic mean? The arithmetic mean is fully compensatory: any deficit on one dimension can be perfectly offset by a surplus on another. This is inappropriate for a development framework where the failure to absorb

labour (HCI), for example, cannot be neutralised by favourable demographics (DSI) — both are necessary conditions for harnessing the dividend. The geometric mean is partially non-compensatory and therefore more theoretically coherent for this application.

Why Z-scores and not Min-Max? Min-Max normalisation anchors the scale to the observed extremes of the sample. Adding a new year of data as any longitudinal study eventually must — reshuffles all historical scores, because the minimum and maximum may change. Z-score normalisation avoids this range-locking problem and, crucially, preserves the correlation matrix that PCA requires for valid eigendecomposition.

Why PC1 absolute loadings for weights, not all retained PCs? Using PC1 alone is a deliberate parsimonious choice. PC1 captures the dominant dimension of co-movement — the main structural trend in each index over 2000–2024. Using multiple PCs would bring in dimensions of variation that are harder to interpret theoretically and would dilute the connection between the weights and the primary developmental narrative that each index is designed to tell.

Why OLS regression imputation and not mean substitution? Mean substitution assumes that missing values are best estimated by the average of observed values. For a trending time series — where virtually every development variable in India shows a clear upward or downward trajectory across 2000–2024, this assumption is directly contradicted by the data. OLS regression imputation uses the structural relationship between variables to generate trend-consistent imputed values, which is analytically superior and transparent.

Why HC1 and not classical OLS standard errors? With only 25 observations spanning periods of extreme economic stress (2008–09, 2020–21) and rapid growth (2003–08), error variance is almost certainly not constant across years. Classical standard errors, which assume homoskedasticity, would overstate precision in volatile years and understate it in stable years. HC1 corrects this without imposing any parametric assumption about the heteroskedastic process.

These choices, taken together, constitute a methodological framework that is both internally consistent and empirically appropriate for the specific character of India's annual development data across 2000–2024.

Chapter 4
The Economic Growth Index (EGI)

4.1 Conceptual Foundation: What the EGI Measures and Why it matters?

The Economic Growth Index (EGI) is the dependent variable at the heart of this study's analytical framework. It is designed to answer one question with precision: how well did India's economy actually perform each year from 2000 to 2024, across the full breadth of its economic activities? The emphasis on *breadth* is deliberate. Reducing economic growth performance to a single indicator — most commonly GDP per capita growth — is a long-standing methodological shortcut that sacrifices informational richness for computational convenience. An economy can register impressive GDP growth while its investment rate is collapsing, its industrial base is contracting, its financial sector remains shallow, and households are spending down savings rather than building wealth. A single GDP figure would tell the observer none of this. The EGI is constructed to correct that deficiency.

Nardo, Saisana, Saltelli, Tarantola, Hoffmann, and Giovannini (2008), in the *OECD Handbook on Constructing Composite Indicators*, articulate the foundational rationale for multidimensional composite indices: they "summarize complex, multi-dimensional realities... [and] are recognized as useful in policy analysis and public communication." For a study that seeks to understand whether India has harnessed its demographic dividend — a structural transition that should manifest across output, investment, trade, industrial production, financial depth, savings behaviour, and household consumption simultaneously — a composite index is not merely convenient. It is the only appropriate instrument.

The EGI's conceptual mandate is tightly bounded: it measures *realized economic growth outcomes* — the things that happen as a consequence of demographic, institutional, and macroeconomic forces, not the forces themselves. In the study's regression model, the five independent indices (DSI, DQI, SDI, HCI, MVI) represent the structural conditions and enabling environment. The EGI represents the outcome they produce. This distinction is not merely theoretical — it is an econometric requirement. If the dependent variable and the independent variables measured the same underlying phenomenon, the OLS error term would be correlated with the regressors, producing biased and inconsistent estimates. Every variable in the EGI was therefore selected with an explicit *endogeneity firewall*: the causal arrow runs from the independent indices toward the EGI variable, not in the reverse direction or in a simultaneous loop.

4.2 The Ten Variables of the EGI: Structure and Sub-Dimensions

The EGI aggregates ten annual time-series variables for India from 2000 to 2024, each capturing a distinct sub-dimension of economic growth performance. These ten variables are not an arbitrary collection — they span eight theoretically identified sub-domains: output and income, physical capital formation, export performance, trade integration, foreign capital attraction, industrial output, financial deepening, domestic savings, and household consumption. Together they constitute a nearly complete map of how a developing economy's growth manifests in measurable form.

Table 3 EGI Variables, the sub dimensions and direction of the variables

Variable	Sub-Dimension	Direction
GDP per capita growth (annual %)	Output & Income	Higher = better
Gross fixed capital formation (% of GDP)	Investment	Higher = better
Exports of goods and services (% of GDP)	Trade Performance	Higher = better
Trade (% of GDP)	Trade Integration	Higher = better
FDI net inflows (% of GDP)	Foreign Capital	Higher = better
Percentage Growth of IIP	Industrial Output	Higher = better
Manufacturing, value added (% of GDP)	Industrial Structure	Higher = better
Domestic credit to private sector (% of GDP)	Financial Deepening	Higher = better
Gross domestic savings (% of GDP)	Savings Capacity	Higher = better
Final consumption expenditure (% of GDP)	Household Welfare	Higher = better

Each variable is discussed in detail below, with its theoretical justification, its relationship to India's specific development experience, and its connection to the foundational growth economics literature.

4.3 Variable-by-Variable Literature Review

4.3.1 GDP Per Capita Growth (Annual %)

GDP per capita growth is the most direct and widely used summary measure of an economy's year-on-year improvement in average material living standards. It answers the foundational question: is the average Indian producing and earning more in real terms than the previous year? The *real* component is critical — this variable strips out inflation by measuring output at constant prices, ensuring that apparent growth in nominal rupees does not conceal stagnation in actual productive capacity.

The theoretical basis for treating GDP per capita growth as the primary economic outcome indicator runs directly through the foundations of modern growth economics. Solow (1956), in his landmark paper "A Contribution to the Theory of Economic Growth," established the neoclassical growth model in which the steady-state level of output per worker — and therefore per capita income — is determined by the saving rate, population growth, and technological progress. Solow's model makes output per capita the variable to be explained by all other structural forces, establishing the conceptual precedent for its role in this study. Mankiw, Romer, and Weil (1992) extended Solow's framework by incorporating human capital and empirically tested it across 98 countries, concluding that "an augmented Solow model that includes accumulation of human as well as physical capital provides an excellent description of the cross-country data." Throughout their analysis, per capita GDP growth is the dependent outcome driven by structural conditions — exactly the analytical role it plays in the EGI.

Barro (1991), in "Economic Growth in a Cross Section of Countries," used average annual per capita GDP growth as his primary dependent variable, explicitly noting that "a country's per capita growth rate tends to be inversely related to its initial level of income per person" — a catch-up growth mechanism of direct relevance to India's development trajectory. Aghion and Howitt (1992), in their Schumpeterian model of endogenous growth, frame output growth as the measurable consequence of innovation inputs, writing that "both the average growth rate and the variance of the growth rate are increasing functions of the size of innovations, the size of the skilled labor force, and the productivity of research" — confirming that growth is a downstream outcome of structural determinants, not a cause. For India's data, this variable ranges from −6.69% (COVID-19 contraction in 2020) to +8.79% (the post-COVID rebound in 2021), with the 2004–2008 boom registering consistently above 6%.

4.3.2 Gross Fixed Capital Formation (% of GDP)

Gross Fixed Capital Formation (GFCF) measures the annual addition to the economy's stock of durable productive assets — machinery, equipment, buildings, transport

infrastructure, and other fixed assets — expressed as a proportion of GDP. It is the economy's investment rate: the share of current output that is being ploughed back into expanding and improving future productive capacity. An economy investing 35% of its GDP in fixed assets is building future production capacity at a dramatically faster rate than one investing only 25%.

The inclusion of GFCF in the EGI rests on one of the most robustly confirmed relationships in growth economics. Levine and Renelt (1992), in their comprehensive robustness analysis of cross-country growth regressions, found "a positive, robust correlation between growth and the share of investment in GDP" — the single most reliably significant variable in the empirical growth literature. Mankiw, Romer, and Weil (1992) demonstrated that "an increase of 10 percentage points in the investment share raises the steady-state income by roughly 20 percent," establishing the quantitative magnitude of the investment-growth link. Aschauer (1989), examining the productivity effects of public capital, found that the public capital stock is "dramatically more important in determining productivity" than previously recognised, validating the inclusion of public investment within the aggregate GFCF measure.

For India, GFCF as a percentage of GDP rose from approximately 26% in 2000 to a peak of nearly 36% in 2007, capturing the investment boom of the high-growth decade. The subsequent decline — falling to 27–28% range after 2012 and through the 2016–2019 period — reflects the well-documented twin balance sheet problem, where over-leveraged corporate balance sheets and stressed bank NPAs suppressed new investment. The COVID year 2020 recorded the lowest GFCF ratio of the sample period, at 27.3%, before recovering to 31.2% by 2022.

4.3.3 Exports of Goods and Services (% of GDP)

Exports of goods and services as a percentage of GDP measure the economy's success in selling its production to the rest of the world, relative to its own size. This variable captures the *external demand dimension* of growth: the degree to which Indian producers are competitive enough — in price, quality, and reliability — to attract and sustain foreign buyers.

The export-led growth hypothesis, formalized by Balassa (1978) in "Exports and Economic Growth: Further Evidence," established that export expansion is strongly associated with GDP growth across developing countries. Michaely (1977) provided one of the earliest empirical demonstrations, showing that "the correlation between export and GNP growth rates is significant." Sachs and Warner (1995) extended this logic to full trade openness, finding that "open economies with high export-to-GDP ratios achieve dramatically higher growth rates," a finding of direct relevance to India's post-1991 liberalisation experience. Grossman and Helpman (1991), in *Innovation and*

Growth in the Global Economy, provided the theoretical microfoundation: integration into world trade accelerates technological learning and productivity growth, making exports simultaneously an outcome of competitiveness and a channel for further improvement.

India's exports as a share of GDP rose from 13.0% in 2000 to a peak of 25.4% in 2013, reflecting the dramatic expansion of both merchandise and services exports following liberalisation. The data also captures the contractions associated with the 2008–09 Global Financial Crisis and the COVID shock of 2020, validating the variable's sensitivity to both domestic competitiveness and external demand conditions.

4.3.4 Trade (% of GDP) - Trade Integration

Trade openness — the sum of exports and imports of goods and services divided by GDP — is the broadest measure of an economy's integration into global commerce. While the exports variable (above) captures the supply-side performance dimension, trade openness captures the *depth of bilateral integration*: how much of India's economic life is connected to global markets in both directions.

Frankel and Romer (1999), in the landmark paper "Does Trade Cause Growth?", used geographic instrumental variables to establish a causal channel from trade to income, finding "a quantitatively large and robust... positive effect on income." Their methodology — isolating the component of trade driven by geography rather than policy — provides the cleanest available estimate of the trade-income relationship. Levine and Renelt (1992) identified the trade-to-GDP ratio as one of the most robust correlates of growth alongside the investment share: "a positive, robust correlation between growth and... the ratio of international trade to GDP." Rodrik, Subramanian, and Trebbi (2004) placed trade integration as an outcome downstream of institutional quality, confirming its status as a realized performance dimension rather than a policy lever.

India's trade openness (total trade as % of GDP) rose from 26.9% in 2000 to a peak of 55.8% in 2012, reflecting the full integration of the post-liberalisation economy into global supply chains. The subsequent moderation — falling to 37.8% during COVID-19 in 2020 — captures the global trade collapse and India-specific demand compression, while the recovery to 50.1% by 2022 and stabilisation around 44–45% in 2023–2024 reflects the return to normal trade flows.

4.3.5 FDI Net Inflows (% of GDP)

Foreign Direct Investment (FDI) net inflows measure the net flow of foreign capital into Indian businesses — equity stakes, greenfield investments, and reinvested earnings — relative to the size of the economy. FDI is qualitatively distinct from portfolio investment: it brings not only capital but also technology, management

practices, global supply chain connections, and competitive pressure. For a developing economy like India, attracting FDI is a signal that the world's most discerning investors find the country's business environment, market potential, and institutional framework sufficiently attractive to commit long-term productive capital.

Borensztein, De Gregorio, and Lee (1998), in "How Does Foreign Direct Investment Affect Economic Growth?", established the foundational empirical case: "FDI is an important vehicle for the transfer of technology, contributing to growth in larger measure than domestic investment. Moreover, we find that there is a strong complementary effect between FDI and human capital." Grossman and Helpman (1991) provided the theoretical grounding, modelling FDI as the primary mechanism through which technological innovations diffuse from advanced to developing economies. Levine (2005), in the *Handbook of Economic Growth*, confirmed that "better developed financial systems attract more external capital," linking financial deepening (V8 below) to foreign capital attraction.

India's FDI net inflows rose from a modest 0.77% of GDP in 2000 to a peak of 3.62% in 2008, then settled in the 1.5–2.5% range through most of the 2010s. The COVID period surprisingly showed elevated FDI (2.41% in 2020) as global investors rotated capital toward India's digital and pharmaceutical sectors, before moderating to 0.69% by 2023.

4.3.6 Percentage Growth of the Index of Industrial Production (IIP)

The Index of Industrial Production measures the volume of output generated by India's industrial sector — mining, manufacturing, and electricity — relative to a base year (currently 2011–12 = 100). The annual percentage growth of this index captures how rapidly industrial production is expanding or contracting each year. Industrial growth is a core performance dimension for a developing economy because industry absorbs surplus agricultural labour, creates scale economies, generates backward and forward linkages across supply chains, and forms the production base for export diversification.

Schumpeter (1911/1934), in *The Theory of Economic Development*, established that innovation-driven industrial transformation is the engine of economic development — entrepreneurial innovation disrupts existing production methods and expands industrial output. IIP growth is the aggregate measurable outcome of this process. Virmani (2004), analysing India's growth phases, used IIP as a key performance metric, confirming that "India's trend growth rate of industrial production shifted upward after economic reforms, driven by changes in the economic environment." Goldar and Kumari (2003) demonstrated that trade liberalisation in the 1990s "favourably affected productivity growth" in Indian manufacturing — with the resulting production expansion captured in IIP growth.

India's IIP growth data reveals the clear imprint of structural events: peak growth during the 2004–2008 investment boom (5.8% annually), contraction in 2013 (−0.1%) and 2019 (−0.8%) during pre-COVID slowdowns, a severe collapse to −8.4% in 2020 during COVID-19, and an extraordinary rebound to 11.4% in 2021 as factories reopened and pent-up orders were fulfilled.

4.3.7 *Manufacturing, Value Added (% of GDP)*

Manufacturing value added as a share of GDP measures the structural weight of the manufacturing sector within the economy — the net contribution of all manufacturing activity, after subtracting the cost of raw material inputs, expressed relative to total GDP. This is a stock-flow hybrid: it measures not just short-run production activity (captured by IIP growth) but the *structural importance* of manufacturing in India's economic architecture over time.

The centrality of manufacturing to development is among the best-established themes in development economics. Thirlwall (1983) developed the balance-of-payments constrained growth model, identifying manufacturing as the engine of sustainable long-run growth through its superior productivity, export potential, and capacity for learning-by-doing. Lucas (1988), in "On the Mechanics of Economic Development," emphasized that "learning-by-doing" in manufacturing drives productivity growth: the structural shift from agriculture to manufacturing is the mechanism through which developing economies escape low-productivity traps. Aghion and Howitt (1992) linked manufacturing expansion directly to the Schumpeterian innovation process — vertical innovations generated by competitive research manifest as expanding manufacturing value added at the sectoral level.

India's manufacturing value added as a share of GDP has exhibited a troubling secular decline in this dataset: from 15.9% in 2000 to a peak of approximately 17.3% in 2006, followed by a sustained downward drift to 12.6% by 2024. This trajectory — rising service sector dominance alongside a stagnant or declining manufacturing share — is at the centre of India's "premature deindustrialisation" debate (Rodrik, 2016) and represents one of the EGI's most policy-sensitive dimensions.

4.3.8 *Domestic Credit to Private Sector (% of GDP)*

Domestic credit to the private sector measures the total stock of loans, advances, and other credit extended by the banking system to private borrowers — firms and households — expressed as a percentage of GDP. It is the standard measure of *financial depth*: the extent to which the financial sector is actively channeling savings into productive private investment and consumption. A financially deep economy enables entrepreneurs to fund ideas beyond their own equity, households to smooth consumption across the lifecycle, and firms to invest in capacity that short-run cash flows could not support.

King and Levine (1993), in the landmark paper "Finance and Growth: Schumpeter Might Be Right," provided the foundational empirical demonstration across 80 countries: "various measures of the level of financial development are strongly associated with real per capita GDP growth, the rate of physical capital accumulation, and improvements in the efficiency with which economies employ physical capital." Levine (2005) confirmed this relationship across an expanded literature, noting that "the preponderance of evidence suggests that both financial intermediaries and markets matter for growth." Roubini and Sala-i-Martin (1992) approached the relationship from the opposite direction, showing that "financial repression has negative consequences for growth" — a low credit-to-GDP ratio reflects suppressed financial intermediation that constrains investment and productivity.

India's domestic credit to private sector rose strongly from 28.3% of GDP in 2000 to a peak of 52.4% in 2013, capturing the substantial deepening of India's banking sector during the liberalisation era. A notable discontinuity in the series occurred around 2016–2017, where the data drops from approximately 51–52% to 38%, likely reflecting methodological reclassification and the NBFC sector's growing prominence. The series recovers toward 40% by 2024.

4.3.9 Gross Domestic Savings (% of GDP)

Gross domestic savings — the share of national income saved rather than consumed by all institutional sectors combined (households, corporates, and government) — is the economy's own internal financing capacity for investment. It is the domestic pool of resources available to fund capital formation without relying on foreign borrowing. The savings rate is both a performance outcome in its own right and the enabling condition for India's investment boom: the remarkable savings surge from 24% of GDP in 2000 to 34% by 2007 was the domestic counterpart of the investment boom measured by GFCF.

Modigliani (1986), in his Nobel Prize lecture, established the life-cycle hypothesis as the foundational theoretical framework: "differences between countries in their saving rates can be explained by differences in the rate of growth of income and in the age distribution of the population." This insight connects the EGI's savings variable directly to the DSI's demographic structure: as India's working-age share rises (rising DSI), the aggregate savings rate should follow — the demographic dividend's savings channel. Athukorala and Sen (2004), in the most comprehensive India-specific analysis, found that "the saving rate rises with both the level and the rate of growth of disposable income" confirming that savings is a downstream outcome of income performance. Harrod (1939), in his foundational growth model, formalized the savings-growth relationship: the warranted growth rate equals the savings rate divided by the capital-output ratio, making the savings rate a structural performance metric in its own right.

India's gross domestic savings rate peaked at 34.4% of GDP in 2007 and has since declined to 28–29% in recent years, reflecting the well-documented fall in household financial savings as a proportion of income a structural concern for India's future investment financing capacity.

4.3.10 Final Consumption Expenditure (% of GDP)

Final consumption expenditure as a share of GDP measures the proportion of national output that is absorbed by household and government consumption goods and services that are used up in the current period rather than saved or invested. In this index, it captures the *demand-side absorption dimension* of economic activity: the extent to which economic growth is translating into actual spending by households and the state.

The consumption share in the EGI is directionally coded as higher = better, reflecting the welfare interpretation: higher consumption expenditure as a share of GDP — in the context of strong overall growth - signals that output expansion is generating real improvements in living standards for the population rather than being entirely absorbed by investment. Ahluwalia (2000), using consumption-based measures as the ultimate development outcomes in the Indian context, established consumption per capita as the downstream welfare realization of structural growth. Datt and Ravallion (1998) demonstrated that "farm output growth and non-farm growth translate into consumption gains for the poor," confirming the causal direction from growth drivers to consumption outcomes. Athukorala and Sen (2004) linked consumption behaviour directly to the life-cycle consumption function — income growth and demographic structure are the determinants; consumption growth is the outcome.

India's final consumption expenditure as a share of GDP has moved inversely to the investment boom: declining from 75.7% in 2000 to 65.6% at the 2007 investment peak, as more output was channeled into capital formation. The subsequent increase rising

back to 72.7% in 2020 during COVID as investment collapsed and partial retreat to 71.4% by 2024 traces the investment cycle's mirror image in consumption *patterns*.

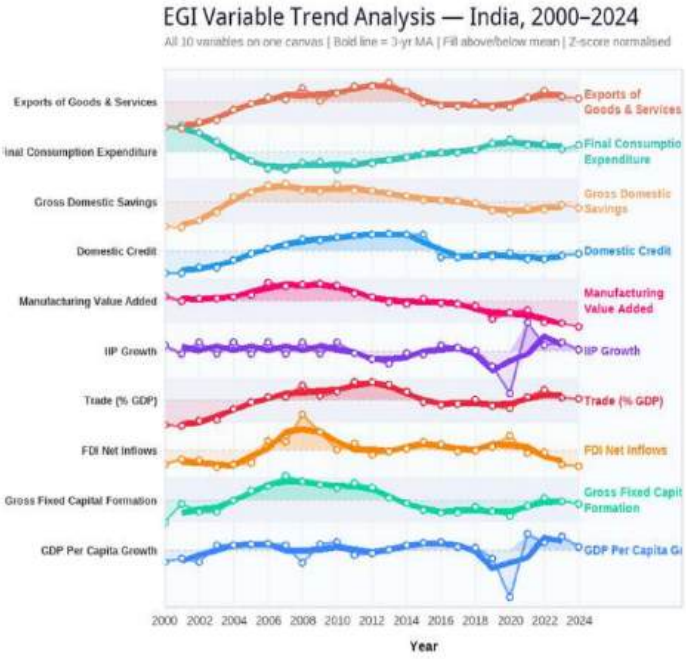


Figure 1 EGI variables Trend Analysis (2000 – 2024)

4.4 The EGI as an Integrated Signal: What the Composite Tells Us

The power of the EGI lies not in any individual variable but in their combination. No single variable can carry the full meaning of economic growth performance. GDP per capita growth can be high in a commodity boom even as investment collapses. Exports can surge while domestic consumption stagnates. Industrial production can expand while financial depth remains shallow. The composite index is designed to capture the co-movement or divergence of these dimensions simultaneously.

A high EGI score in any given year indicates that India's economic performance was above its own long-run average across *multiple* dimensions simultaneously not just on one or two. The PCA-weighted geometric mean aggregation (described in Chapter 3) ensures that excellence on one variable does not mask failure on another: a year with very strong GDP growth but collapsing investment and falling exports would receive a lower composite score than a year with moderately strong performance across all dimensions. This partial non-compensability is the key analytical feature that distinguishes the EGI from a simple GDP-based measure.

In the regression model, the EGI is the variable that the five independent indices DSI, DQI, SDI, HCI, and MVI collectively explain. A positive coefficient on an independent index means that years of stronger performance on that index tend to coincide with higher EGI scores across the full suite of growth dimensions. The regression therefore tests whether India's demographic dividend has translated not into GDP growth alone, but into comprehensive economic performance investment, trade, industrialisation, financial depth, savings, and household welfare together.

The EGI data for India from the sample period reveals several structural patterns worth noting at the outset. The composite rises from a baseline of 3.07 in 2000 to a peak of 5.89 around 2008, capturing the multi-dimensional boom of the high-growth decade. It then exhibits a clear growth slowdown through 2012–2016, followed by recovery and the COVID shock of 2020. The mean EGI score of 4.71 (median: 4.59) with a coefficient of variation of 17.5% confirms moderate volatility around a steadily rising baseline consistent with India's aggregate growth story, but with considerable within-period variation that the regression will attribute to the dynamics of the five independent indices.

4.5 Data Source

All ten variables constituting the EGI are drawn from publicly verifiable, institutionally authoritative sources. The primary source for GDP per capita growth, GFCF, exports, trade openness, FDI, manufacturing value added, domestic credit, gross domestic savings, and final consumption expenditure is the **World Bank World Development Indicators (WDI)** database, which provides pre-computed annual series for India at consistent constant-price definitions. The IIP growth rate series is drawn from the **Ministry of Statistics and Programme Implementation (MoSPI)** monthly IIP releases, compiled into annual (April–March) averages. All series span 2000 to 2024 continuously. Where gaps exist in early-period observations, the OLS regression imputation method described in Chapter 3 was applied.

4.6 Why These Ten: Variable Selection Logic and Exclusions

The OECD Handbook's Step 2 (Nardo et al., 2008, 1.2) requires the researcher to document not only which variables were selected, but also why alternatives were rejected. For the EGI, a comprehensive longlist of over 40 possible variables was assembled spanning all sub-dimensions of economic growth performance, before the final 10 were selected. The exclusion decisions are as consequential as the inclusions and deserve explicit justification.

Real GDP growth rate versus GDP per capita growth rate: The EGI uses GDP *per capita* growth rather than aggregate GDP growth. The distinction matters: India's population grows at approximately 1% per year. A country that grows its aggregate GDP by 1.5% annually but whose population grows at 1% is barely improving average living standards. Using per capita growth correctly credits the economy for the net improvement in each citizen's productive output, not merely the population-weighted expansion of the aggregate. This choice aligns with Barro (1991), Mankiw, Romer, and Weil (1992), and Solow (1956), all of whom use per capita measures as the standard dependent variable.

Trade openness versus current account balance: The current account balance (surplus or deficit as a share of GDP) was considered as an alternative to trade openness. It was rejected because a surplus can reflect either strong competitiveness (high exports relative to imports) or compressed domestic demand (low imports due to recession) — two diametrically opposite economic conditions producing the same number. Trade openness is a more neutral and informative measure of integration depth.

Domestic credit versus stock market capitalisation: Stock market capitalisation as a share of GDP was considered as an alternative financial depth measure. It was excluded for two reasons: first, India's equity market is smaller and less representative of the full financial system than in developed economies; second, market capitalisation is highly volatile in ways that reflect valuation changes (price-earnings multiples) rather than genuine changes in financial intermediation depth. Domestic credit to the private sector is a more stable, policy-neutral measure of the banking system's intermediation activity.

Manufacturing value added versus services value added: The services sector was considered as an alternative sub-dimension, given India's distinctive service-led growth model. The manufacturing variable was retained over services because the existing literature — Thirlwall (1983), Lucas (1988), Kaldor's growth laws — establishes manufacturing as the structurally more important sector for employment absorption and export diversification in developing economies. Moreover, India's policy debate on the "missing middle" of manufacturing makes the manufacturing

share a more diagnostic and policy-relevant EGI dimension than the already-dominant services share.

IIP growth versus GVA growth in industry: The Index of Industrial Production was selected over the broader GVA (Gross Value Added) growth in industry because IIP is a *volume* measure — it tracks actual physical production quantities, not the monetary value added which can be inflated by price changes. For tracking industrial output performance independent of pricing effects, IIP growth is the more accurate indicator.

Gross domestic savings versus household savings: Household savings alone were considered as a narrower alternative. Gross domestic savings was selected instead because it captures the full institutional scope — household, corporate, and government savings collectively constitute the economy's domestic investment financing capacity. Since India's corporate savings boom in the 2000s was as important to the investment surge as household savings, using the aggregate measure is more theoretically appropriate.

The selection of these ten variables, therefore, is not arbitrary. It reflects the application of four criteria consistently: analytical soundness grounded in the growth economics literature; measurability through annual institutional data from 2000 to 2024; absence of overlap with the five independent indices that would create endogeneity; and conceptual breadth across the eight sub-dimensions of India's growth performance. The result is an Economic Growth Index that captures, with fidelity and balance, what it meant for India's economy to grow or to fail to grow across the 25 years of the study period.

4.7 Descriptive Overview of the EGI

Before the regression analysis, it is analytically useful to understand the descriptive trajectory of the composite EGI score across the 2000–2024 period. The following patterns emerge from the constructed index:

Central tendency: The EGI's 25-year mean score of 4.71 (median: 4.59) indicates that India's economic performance was broadly consistent and moderately strong across the sample period, with the median year performing close to the mean — suggesting a roughly symmetric distribution without extreme outliers dominating the average.

The growth peak (2007–2008): The EGI attains its maximum score around 2007–2008, corresponding to India's high-growth decade when GDP per capita growth exceeded 6%, GFCF peaked at 35–36% of GDP, exports surged, FDI reached 3.6% of GDP, and gross domestic savings crossed 34% of GDP. All ten EGI dimensions moved favorably simultaneously an event that the geometric mean aggregation identifies clearly because it rewards co-movement across dimensions.

The post-crisis moderation (2012–2016): The EGI registers a sustained decline through this period, consistent with the collapse of the investment cycle, the twin balance sheet stress of over-leveraged corporates and NPL-burdened banks, sluggish export growth, and declining gross savings rates. No single indicator tells this story completely the EGI's composite signal captures the breadth of the slowdown.

The COVID shock (2020): The year 2020 produces the EGI's lowest composite score, driven by the simultaneous collapse of GDP per capita growth (−6.7%), IIP growth (−8.4%), and GFCF, with only FDI showing unexpected resilience. The geometric mean's partial non-compensability means this multi-dimensional collapse is appropriately penalised in the composite, rather than being masked by any single dimension's stability.

The coefficient of variation (17.5%) reflects moderate volatility enough to capture meaningful cyclical variation in India's economic performance, but not so extreme as to be dominated by a single shock-year. This range of variation is what makes the subsequent regression analysis informative: there is genuine signal in the EGI's annual movements for the independent indices to explain.

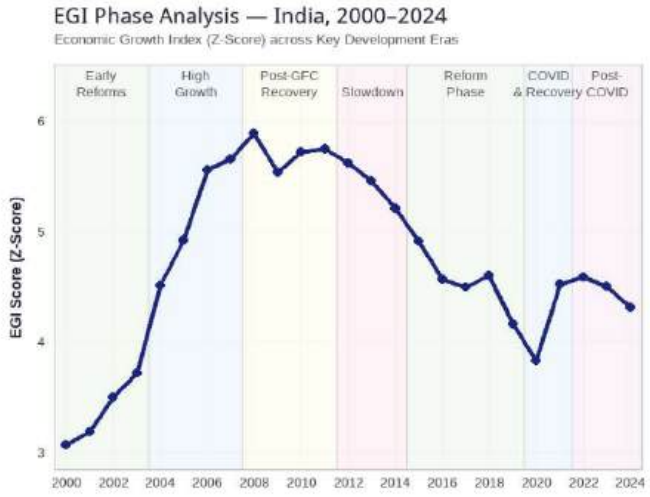


Figure 2 EGI Phase Analysis (2000 – 2024)

Chapter 5
The Demographic Structure Index (DSI)

5.1 Conceptual Foundation: What the DSI Measures and Why it matters?

The Demographic Structure Index (DSI) is the first of five independent variables in this study's regression model, and it is, in a fundamental sense, the variable closest to the study's central question. India's demographic dividend — the subject of the entire research — is not an abstract concept. It is a structural phenomenon: a specific phase of population change in which the working-age cohort expands relative to the dependent population, creating the potential for accelerated per capita economic growth. The DSI is designed to measure precisely this structural phenomenon — to capture the shape, age composition, fertility and mortality dynamics, gender balance, and urbanisation trajectory of India's population as it moves through its demographic transition from 2000 to 2024.

The conceptual mandate of the DSI is both precise and bounded. It measures only the *structural or compositional* characteristics of the population — not its quality (which is the domain of the DQI), not its social equity (the SDI), not its labour market activation (the HCI), and not the macroeconomic environment (the MVI). This constraint is not methodological housekeeping — it is an econometric necessity. In the OLS regression model that forms Stage Two of this study's methodology, the DSI is a regressor: a variable that is supposed to cause variation in the EGI. If the DSI incorporated outcomes that are jointly determined with economic development — such as income-driven urbanisation or health-expenditure-driven improvements in child survival the OLS estimator would suffer from simultaneity bias, rendering the coefficient estimates inconsistent.

The intellectual foundation for the DSI rests on the demographic transition theory, first systematically articulated by Frank Notestein (1945) as a description of society's progression from a pre-modern regime of high fertility and high mortality to a modern regime in which both are low. Superimposed on this theoretical bedrock is the demographic dividend hypothesis, formalised by Bloom and Williamson (1998) in *The World Bank Economic Review*, who demonstrated that East Asia's economic miracle "occurred in part because East Asia's demographic transition resulted in its working-age population growing at a much faster rate than its dependent population during 1965–90, thereby expanding the per capita productive capacity of East Asian economies." This insight — that population *structure*, rather than population *size*, is the primary demographic driver of growth — forms the conceptual spine of the DSI.

5.2 The Ten Variables of the DSI: Structure and Sub-Dimensions

The DSI aggregates ten annual time-series variables for India, each capturing a distinct sub-dimension of demographic structure. These variables span four analytically separable domains: age composition, fertility dynamics, mortality transition, and spatial structure (urbanisation) and gender balance.

Table 4 DSI Variables, the sub dimensions and direction of the variables

Variable	Sub-Dimension	Direction
Population ages 15–64 (% of total population)	Age Structure / Working-Age Base	Higher = better
Fertility rate, total (births per woman)	Fertility Dynamics	Lower = better (inverted)
Age dependency ratio (% of working-age population)	Total Dependency Burden	Lower = better (inverted)
Birth rate, crude (per 1,000 people)	Birth Dynamics	Lower = better (inverted)
Death rate, crude (per 1,000 people)	Mortality Transition	Lower = better (inverted)
IMR (per 1,000 live births)	Child Survival / Fertility Driver	Lower = better (inverted)
Urban population (% of total population)	Spatial Structure	Higher = better
Sex Ratio at Birth (female live births per 1,000 male)	Gender Balance	Higher = better
Age dependency ratio, old (% of working-age population)	Ageing Pressure	Lower = better (inverted)
Population growth (annual %)	Population Momentum	Lower = better (inverted)

Note: Variables marked as "inverted" undergo the direction-alignment transformation $x' = \max(x_i) + \min(x_i) - x_{it}$ described in Chapter 3, so that higher values consistently indicate more favourable demographic structure before normalisation and aggregation.

5.3 Variable-by-Variable Literature Review

5.3.1 Population Ages 15–64 (% of Total Population) - Working-Age Share

The working-age population share (WAPS) is the proportion of India's total population that falls within the 15–64 age bracket — the economically productive cohort capable

of participating in the labour force, earning income, paying taxes, and generating the savings that fuel capital accumulation. It is not an exaggeration to say that this single variable is the statistical representation of the demographic dividend itself: when WAPS rises, the worker-to-dependant ratio improves, and the first demographic dividend window opens.

The theoretical foundation is as deep as modern growth economics. Bloom and Williamson (1998), in their landmark analysis of East Asia's economic miracle, found that demographic change — specifically the expansion of the working-age share relative to the dependent population — explained "one-quarter to two-fifths of East Asia's economic growth" in the high-growth decades. Aiyar and Mody (2011), in an IMF Working Paper applying the same framework specifically to India's states, found that "there is a large and significant growth impact of both the level and growth rate of the working-age ratio," with demographic change accounting for "between 40 to 50 percent of India's growth acceleration since the 1980s." Choudhry and Elhorst (2010) confirmed that "GDP per capita growth is positively related to the growth differential between the working-age population and the total population," explaining 39% of per capita GDP growth in India over 1961–2003.

India's WAPS rose from 60.0% in 2000 to 68.2% in 2024 — an increase of 8.2 percentage points in 24 years, representing the structural materialisation of the dividend window. The endogeneity firewall is airtight: the working-age population in any given year consists of people born 15 to 64 years earlier. India's GDP per capita in 2015 cannot have caused the births that occurred between 1951 and 2000. The multigenerational lag decisively breaks any contemporaneous feedback loop.

5.3.2 Fertility Rate, Total (Births per Woman) - Total Fertility Rate

The Total Fertility Rate (TFR) answers the hypothetical question: if a woman were to live through her entire reproductive lifespan subject to the age-specific fertility rates prevailing in a single given year, how many live births would she have in total? A TFR of 2.1 is the universal replacement-level fertility — the level at which a generation exactly replaces itself. A TFR above 2.1 means the population will grow in the long run; below 2.1 means eventual stabilisation and decline.

The TFR's inclusion in the DSI reflects its centrality to demographic transition theory. Notestein (1945) identified the fertility decline as the defining second phase of the demographic transition — following the earlier fall in mortality — and described it as the mechanism through which the demographic dividend window opens. Bloom and Williamson (1998) showed that the fertility decline in East Asia "is more dramatic during the twentieth century than in any other region or historical period and contributed substantially to East Asia's economic miracle." Kelley and Schmidt (1995), studying 89 countries from 1960 to 1995, found that "the positive impacts of density,

size, and labour force entry were swamped by the costs of rearing children and maintaining an enlarged youth-dependency age structure," confirming that fertility reduction is growth-enhancing through the dependency channel. Mankiw, Romer, and Weil (1992) treat population growth — closely linked to TFR — as a structurally exogenous variable in the growth regression.

India's TFR declined from 3.35 births per woman in 2000 to 1.96 in 2024, crossing the replacement level of 2.1 around 2020 — a historic demographic milestone. This continuous decline is the engine driving the narrowing base of India's population pyramid and the consequent expansion of the working-age share measured in Variable 1.

5.3.3 Age Dependency Ratio (% of Working-Age Population) - Total Dependency Burden

The total age dependency ratio measures the number of economically dependent people — those too young (ages 0–14) or too old (ages 65 and above) to typically participate in the formal labour force — per 100 persons of working age (15–64). If the dependency ratio is 60, every 100 workers support 60 dependants from their income. It is the inverse face of the working-age share: as the WAPS rises, the dependency ratio mechanically falls.

The economic significance of the dependency ratio was formalised by Lee and Mason (2006), who articulated the core mechanism: "with fewer people to support, a country has a window of opportunity for economic growth if the right social and economic investments and policies are made." Chaudhry and Elhorst (2010) found that per capita GDP growth is "negatively related to child and old-age dependency ratios," with the dependency ratio effect operating through both the savings channel — families with fewer dependants save more — and the fiscal channel — governments with lower youth dependency spend less on social services and more on productive investment. Bloom, Canning, and Sevilla (2003), in their RAND monograph, confirmed that "population age structure, more than size or growth per se, affects economic development," making the dependency ratio a more discriminating structural variable than aggregate population size.

India's total age dependency ratio fell from 66.6 per 100 working-age persons in 2000 to 46.6 in 2024 — a dramatic 20-point improvement that represents the structural compression of India's dependency burden and the structural opening of the dividend window. This is one of the strongest directional trends in the entire dataset.

5.3.4 Birth Rate, Crude (per 1,000 People) - Birth Dynamics

The Crude Birth Rate (CBR) counts the number of live births occurring in a given year per 1,000 people in the total mid-year population. Unlike the TFR (which controls for

age structure and measures fertility behaviour), the CBR captures the *actual flow* of new births into the population — the direct determinant of future child dependency and population momentum. A declining CBR means fewer children are being born per unit of population, which directly reduces the youth dependency burden and, over 15 years, swells the working-age cohort.

The Sample Registration System's annual CBR series for India provides unbroken coverage from 1971 to the present, making it one of the most consistently available demographic flow variables for the 2000–2024 study period. Barro and Sala-i-Martin (2004), in their comprehensive treatment of growth theory and evidence, include crude demographic rates as structural determinants of growth, treating them as exogenous to short-run income fluctuations. Notestein's (1945) original four-stage demographic transition model makes the decline in birth rates — following the earlier fall in death rates — the central dynamic of the transition, validating CBR's inclusion as a structural DSI variable. Purohit (2023), in a recent study of India's demographic transition, confirms that India's CBR has declined from 36.9 in 1971 to 18.4 in 2023, tracing India's trajectory through the demographic transition with precision.

India's CBR in this dataset falls from 27.5 per 1,000 in 2000 to 16.0 in 2024 — a 42% reduction that, combined with the TFR decline, confirms that India is in an advanced stage of its fertility transition. The endogeneity argument parallels that for TFR: births in year t are biologically determined approximately nine months prior to the observation, and the social decisions driving birth rates reflect cultural and policy factors accumulated over years, not short-run GDP movements.

5.3.5 Death Rate, Crude (per 1,000 People) - Mortality Transition

The Crude Death Rate (CDR) measures the number of deaths per 1,000 persons in the mid-year population. Together with the CBR, the CDR determines the natural rate of population increase. In the context of the DSI, the CDR captures the mortality phase of the demographic transition — the decline in death rates that historically precedes the fertility decline and sets the transition in motion.

Notestein (1945) placed the decline in mortality at the very beginning of the demographic transition: when public health improvements, famine control, and disease prevention reduce death rates while birth rates remain high, the population enters a phase of rapid natural increase before the fertility transition catches up. Lorentzen, McMillan, and Wacziarg (2008) in the *Journal of Economic Growth* examined the death-development relationship across countries, confirming the complex interplay between mortality, institutional quality, and growth. For India specifically, the CDR has been driven primarily by immunisation programs, the expansion of primary healthcare infrastructure, and reductions in communicable disease mortality — factors

that are largely exogenously determined by public health policy rather than year-to-year GDP fluctuations.

India's CDR in this dataset declined from 8.6 deaths per 1,000 in 2000 to 6.6 in 2024, with the notable exception of 2021 (CDR: 9.3), which captures the COVID-19 excess mortality spike. This anomalous year is structurally important — it demonstrates that the CDR variable appropriately captures genuine demographic shocks, and that the DSI's composite score correctly registered a structural deterioration in that year. In direction terms, the CDR is inverted: a lower death rate is coded as a more favourable structural outcome.

5.3.6 IMR (per 1,000 Live Births) - Child Survival and Fertility Driver

The Infant Mortality Rate (IMR) is the number of deaths among children under the age of one year per 1,000 live births. Within the DSI, the IMR is included not as a health outcome variable — that role belongs to the DQI — but as a *demographic structural variable* that shapes both the age composition of the population and the fertility behaviour of families. The theoretical link runs through the child survival hypothesis: in societies with high infant mortality, families produce many births because they know a significant fraction will not survive to adulthood. As IMR falls and parents become confident that their children will survive, they voluntarily reduce desired family size — driving TFR down and initiating the demographic dividend mechanism.

Barro and Sala-i-Martin (2004) treat infant mortality as a lagged structural determinant of growth rather than a contemporaneous health outcome, precisely because the IMR's primary economic channel is through its effect on fertility behaviour — a multigenerational demographic mechanism. Bloom, Canning, and Williamson (1998) embedded infant survival as a key driver of the demographic transition in their age-structured growth model. Kirk (1996), in his comprehensive review of demographic transition theory, established that "the infant mortality rate is the single most powerful predictor of when a society begins its fertility decline," giving the IMR a causal primacy in the transition process that justifies its inclusion as a structural variable.

India's IMR fell from 66.3 per 1,000 live births in 2000 to 23.3 in 2024 — a decline of over 64% in 24 years, representing one of the most dramatic improvements in child survival in India's demographic history. This declining IMR is the structural precondition for India's continuing fertility decline, making it an indispensable component of the DSI's measurement of demographic structural change.

5.3.7 Urban Population (% of Total Population) - Spatial Structure and Urbanisation

Urban population share measures the proportion of India's total population residing in officially classified urban areas. Urbanisation is included in the DSI because it is one

of the most powerful structural expressions of the demographic transition: declining fertility and mortality — especially in rural areas — create surplus agricultural labour that migrates to cities, and urban populations have systematically lower fertility rates and different age-sex compositions (younger, more working-age migrants) than rural populations.

Dyson (2004) articulated the theoretical case most directly: "the demographic transition has been largely responsible for bringing about urbanisation, thus played an important role in facilitating the process of economic growth." Todaro (1969), in his canonical model of rural-urban migration, established that urbanisation is driven by demographic pressure in rural areas and the expectation of higher urban wages — both fundamentally demographic structural forces, not short-run economic outcomes. Sarkar (2019) confirmed in a study of Indian urbanisation that "urbanisation in India is largely driven by demographic momentum and structural economic changes, not year-to-year income fluctuations," supporting the endogeneity firewall. At the national level, urban populations in India exhibit TFR of approximately 1.6 versus rural TFR of 2.1 (SRS 2023), creating a self-reinforcing structural dynamic: as the urban share rises, national fertility falls further, accelerating the demographic transition.

India's urban population share rose from 27.6% in 2000 to 35.4% in 2024 — a gradual structural shift that, while slower than East Asian counterparts, represents a meaningful spatial reallocation of population toward the more demographically mature urban sector. The slow pace of urbanisation in India — approximately 0.3–0.4 percentage points per year — is itself a structurally significant finding for the regression model.

5.3.8 Sex Ratio at Birth (Female Live Births per 1,000 Male) - Gender Balance

The Sex Ratio at Birth (SRB) measures the number of female live births per 1,000 male live births. Biologically, the natural SRB across all human populations is approximately 943–952 females per 1,000 males. Any substantial deviation below this natural range is a demographic fingerprint of son-preference, sex-selective abortion, and female foeticide — practices that distort the age-sex composition of incoming birth cohorts and have long-run structural consequences for population dynamics.

The SRB is included in the DSI because a severely imbalanced SRB creates structural demographic consequences that extend far beyond the immediate birth cohort: as these cohorts age, they create marriage squeezes (insufficient women for marriageable men), potential fertility depression further down the transition, and altered labour market dynamics — all of which affect the working-age age-sex composition that is central to the demographic dividend. UNFPA India (2012) confirmed that India's SRB imbalance reflects deeply embedded social norms around son-preference and access to sex-determination technology, factors that evolve over cultural and generational timescales

independent of short-run GDP movements. The evidence of self-correction of child sex ratios in India (published in PMC) suggests that SRB dynamics respond to cultural norms and future value assessments — not macroeconomic conditions, establishing the exogeneity required for the regression model.

India's SRB rose from 886 female births per 1,000 male births in 2000 to 930 in 2024 — a structural improvement toward the natural value of approximately 943–952, reflecting the impact of awareness campaigns, the PCPNDT Act enforcement, and changing social norms. This improving trajectory contributes positively to the DSI's composite score, capturing the gradual normalisation of birth gender balance.

5.3.9 Age Dependency Ratio, Old (% of Working-Age Population) - Ageing Pressure

The old-age dependency ratio (OADR) measures the number of persons aged 65 and above per 100 persons of working age (15–64). While the total dependency ratio (Variable 3) captures both child and elderly dependency combined, the OADR isolates the *ageing component* of the dependency burden — a distinct and structurally different pressure from child dependency. Child dependency declines as fertility falls; old-age dependency rises as life expectancy improves and as large birth cohorts from the high-fertility past eventually age into retirement.

The OADR is theoretically important because it captures what Lee and Mason (2006) call the "second demographic dividend" challenge: as economies age, the savings and fiscal implications of an expanding elderly population begin to offset the first dividend's benefits. Park, Shin, and Kikkawa (2022), in *Economic Modelling*, found that "a growing share of older people combined with a shrinking working-age population lowers economic growth." Geethu and Nair (2021) documented that India's economic dependency ratio — when adjusted for actual participation rates among the elderly — is "almost three times the nominal old-age dependency ratio," indicating that the structural burden is larger than the headline OADR suggests. For the 2000–2024 period, India's OADR remains relatively modest — rising from 7.3 to 10.5 per 100 working-age persons — reflecting India's still-young population, but the upward trend is structurally significant for what it presages about the post-2035 period.

The endogeneity argument for the OADR is the strongest of all ten variables: the elderly population in year t consists entirely of persons born at least 65 years earlier. India's GDP in 2020 had absolutely no causal effect on the size of the cohort born before 1955. The reverse-causality channel — economic development extending life expectancy — operates over a full lifetime and is entirely irrelevant to contemporaneous OLS endogeneity in a 25-year window.

5.3.10 Population Growth (Annual %) - Population Momentum

The annual population growth rate (APGR) measures the percentage change in India's total population from one year to the next, combining the effects of natural increase (births minus deaths) and net migration. It is the most parsimonious single-number summary of the momentum of India's demographic transition: a high and falling APGR indicates that the transition is underway and that the per capita denominator in all growth calculations is decelerating.

The Solow (1956) growth model makes the population growth rate a central structural variable: because the same aggregate savings must be spread over a larger and larger number of workers as the population grows, a higher population growth rate dilutes the per capita capital stock and depresses per capita income growth. Mankiw, Romer, and Weil (1992) extended this, finding empirically that "holding population growth and capital accumulation constant, countries converge at about the rate the augmented Solow model predicts" — treating the APGR as a structurally predetermined variable in the growth regression. Headey and Hodge (2009), in a meta-regression analysis of 471 regressions from 29 growth studies published in *Population and Development Review*, found that "particularly strong is the evidence in support of the increasingly adverse effects of population growth in the post-1980 period," establishing the causal direction from APGR to growth outcomes unambiguously.

India's APGR declined from 1.88% in 2000 to 0.89% in 2024, with the decline accelerating in the later years of the sample. This deceleration of population growth — the combined consequence of falling TFR and declining CBR — is the aggregate demographic structural indicator of India's transition maturity, complementing and summarising the nine more specific structural variables above.

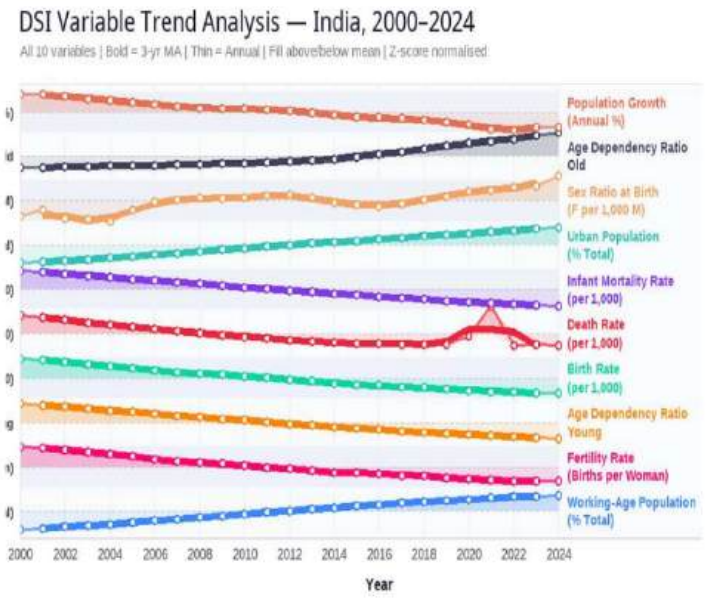


Figure 3 DSI variables Trend Analysis (2000 – 2024)

5.4 What the DSI Composite Signal Tells Us

Taken individually, each of the ten variables above narrates one dimension of India's demographic structural transformation. Taken together through the PCA-weighted geometric mean, they produce the DSI composite score — a single annual number that summarises the overall favourability of India's population structure for economic growth in that year.

A high DSI score in any given year indicates that India's demographic structure was above its own 2000–2024 average across multiple dimensions simultaneously: the working-age share was large, the TFR was low, dependency burdens were compressed, birth and death rates were falling, infant survival was high, urbanisation was advancing, and gender imbalance at birth was improving. The geometric mean's partial non-compensability ensures that weakness on one dimension — for example, a still-elevated APGR — cannot be fully concealed by strength on the working-age share alone.

In the regression model, the DSI's coefficient measures whether years of more favourable demographic structure correspond to years of higher EGI scores — whether the demographic dividend is actually translating into better economic performance across investment, trade, industry, finance, savings, and consumption simultaneously. The theoretical expectation, grounded in Bloom and Williamson (1998), Aiyar and Mody (2011), and Choudhry and Elhorst (2010), is a positive and statistically significant coefficient: more favourable demographic structure should predict stronger comprehensive economic growth performance.

5.5 Descriptive Overview of the DSI Trajectory

India's DSI score more than doubled over the sample period, rising from a baseline of 2.04 in 2000 to a peak of 4.42 in 2023 (mean: 3.47). This is the strongest upward trend among all five independent indices in the study, reflecting the depth and continuity of India's demographic structural improvement across the 2000–2024 period. The consistent upward trajectory — driven by steady growth in the working-age share from 60% to 68%, falling fertility from 3.35 to 1.96, compressing dependency from 66.6 to 46.6, declining IMR from 66.3 to 23.3, and rising urbanisation from 27.6% to 35.4% — confirms that India's population was structurally better positioned for the dividend in each successive year of the sample.

The one notable disruption in this trajectory occurs in 2020–2021, where the COVID-19 pandemic's excess mortality causes an upward spike in the crude death rate (from 6.7 to 9.3 per 1,000 in 2021) — a structural disruption captured in the CDR variable and propagated into the composite score. The otherwise monotonic improvement in DSI across 24 years makes it the most stable and trend-driven of the five independent indices, and sets up the regression's core question: why, despite this sustained structural improvement in demographic conditions, did India's economic growth performance not rise proportionally?

5.6 Data Sources

All ten variables constituting the DSI are drawn from the following primary and supplementary sources:

- **World Bank World Development Indicators (WDI)**: The primary source for all ten variables, providing annual series for India from 2000 to 2024 via series codes (working-age share), (TFR), (total dependency ratio), (crude birth rate), (crude death rate), (IMR), (urban share), (old-age dependency ratio), and (population growth rate).

- **Sample Registration System (SRS), Office of the Registrar General of India**: The gold-standard primary source for India's annual vital rates — CBR, CDR, IMR, TFR, and SRB. The SRS operates via a large-scale stratified random sample of approximately 7,595 sample units covering 7.27 million individuals, producing annual demographic estimates that are used to cross-validate and supplement the WDI series.
- **Census of India Technical Group Population Projections 2011–2036**: Official cohort-component projections for age-structured population variables (working-age share, dependency ratios, APGR) for inter-censal years.
- **UNFPA India** and **SRS Statistical Reports**: Primary source for the Sex Ratio at Birth series, with the SRS Statistical Report providing annual SRB estimates by residence.

5.7 Variable Selection Logic and Exclusions

Following the OECD Handbook's Step 2 discipline, the final ten DSI variables were selected from a longlist of approximately 28 candidate demographic variables. The key exclusion decisions are as follows:

Median age versus working-age share: Median age was considered as an alternative summary of population maturity. It was excluded because it provides less analytical specificity than the working-age share for the demographic dividend hypothesis: two populations with the same median age can have very different working-age shares depending on their exact age pyramids. The 15–64 working-age share directly measures the dividend-generating cohort.

Under-5 mortality rate (U5MR) versus IMR: The under-5 mortality rate was considered as an alternative child survival indicator. IMR was preferred because it is available annually from the SRS with greater precision, and because the IMR-to-fertility feedback mechanism operates primarily through first-year survival (the critical period that determines replacement intentions), making IMR the more theoretically motivated variable.

Youth population share (15–29 %) versus total working-age share: A youth bulge variable was considered as a supplementary age-structure indicator. It was excluded to avoid redundancy with the working-age share: the 15–64 share already captures the youth bulge contribution, and the youth-specific variable would create near-multicollinearity in the PCA step.

Net migration rate: Net migration was excluded because India's net migration rate is near zero and has negligible variation across the 2000–2024 period, contributing no

informational signal to the composite. Including a near-zero flat variable would dilute the PCA's eigendecomposition without adding analytical content.

Child sex ratio (0–6 years, Census) versus Sex Ratio at Birth: The child sex ratio (from Census rounds) was considered as an alternative to the SRB. The SRB was preferred because it is available annually from the SRS, whereas the child sex ratio is only available decennially from Census operations, insufficient frequency for a 25-year annual time series.

These exclusions confirm that the final ten variables are not merely available by convenience but selected by a principled application of the four OECD criteria: analytical soundness, measurability with annual frequency, non-redundancy, and relevance to the specific construct of demographic *structure* as distinct from demographic quality, social outcomes, or labour market performance.

5.8 The DSI in the Regression Framework: Theoretical Expectations

Within the study's regression model, the DSI enters as the structural demographic regressor the variable that operationalises the demographic dividend hypothesis. The expected sign of the DSI's coefficient is unambiguously positive: years in which India's demographic structure was more favourable (higher DSI score) should correspond to years in which India's comprehensive economic growth performance (higher EGI score) was stronger, all else equal.

This expectation is grounded in three decades of empirical literature. Bloom and Williamson (1998) estimated that the working-age share expansion explained 25 to 40% of East Asian economic growth. Aiyar and Mody (2011) attributed 40–50% of India's growth acceleration to demographic change. Choudhry and Elhorst (2010) found that demographic dynamics explained 39% of India's per capita GDP growth from 1961 to 2003. If the DSI coefficient in this study's regression is positive and statistically significant, it provides fresh time-series evidence for India over 2000 – 2024 that is consistent with this established literature.

However, the study's central intellectual contribution is the *comparison* of the DSI coefficient with the coefficients on DQI, SDI, HCI, and MVI. If the DSI coefficient is positive but the DQI or HCI coefficients are weak or negative, the finding would suggest that India has been accumulating favorable demographic structure, the potential of the dividend — without converting it into quality-adjusted human capital or productive employment. The DSI therefore does not stand alone: it is the first independent variable in a five-variable framework designed precisely to test whether demographic potential has been matched by demographic quality, social equity, labour

market capacity, and macroeconomic stability. The answer to that question awaits the regression results presented in Chapter 10.

The DSI is, in this sense, both the opening variable and the central intellectual tension of the study. India's structural demographic story from 2000 to 2024, told through these ten carefully selected, theoretically grounded, and annually measured variables, is one of genuine and sustained improvement: a population transitioning through its dividend window with measurable momentum. Whether that structural improvement translated into the comprehensive economic growth it theoretically enables is the question to which the subsequent chapters and the regression model are dedicated.

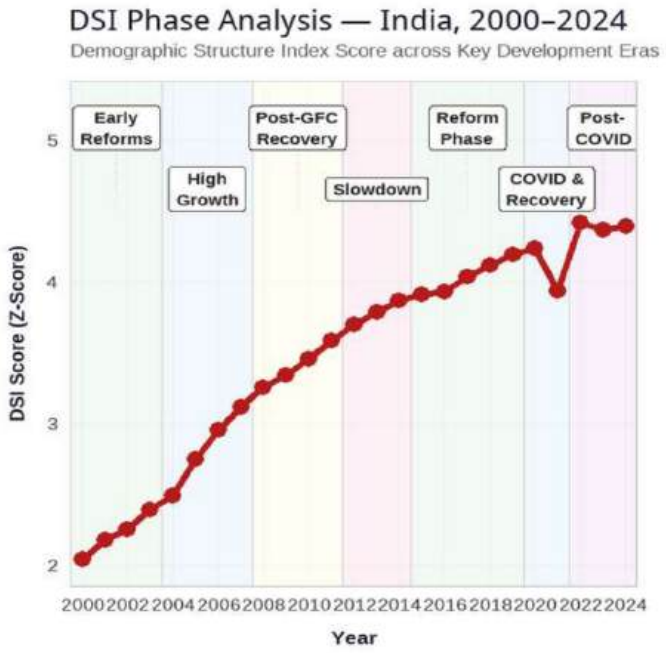


Figure 4 DSI Phase Analysis (2000 – 2024)

Chapter 6
The Demographic Quality Index (DQI)

6.1 Conceptual Foundation: What the DQI Measures and Why it matters?

The Demographic Quality Index (DQI) is the second independent variable in this study's regression model, and it represents the most intellectually significant extension of the conventional demographic dividend literature. If the DSI (Chapter 5) answers the question *how many working-age people does India have?*, the DQI answers the entirely different and more challenging question: *how good is that workforce?* A large working-age population that is malnourished, poorly educated, inadequately immunised, and largely illiterate is not a dividend — it is a demographic burden masquerading as structural advantage. The DQI is built to measure the gap between India's demographic potential (captured by the DSI) and the actual quality of human capital that population embodies.

The conceptual foundation of the DQI rests on the human capital tradition in economics, inaugurated by Schultz (1961), who drew the critical line between the *quantity* and *quality* of human capital, arguing that "investment in human capital is probably the major explanation for this difference" between observed and predicted economic growth. Lucas (1988), in "On the Mechanics of Economic Development," formalised this by placing human capital — defined not as the *number* of workers but as the accumulated "stock of general skills" — at the centre of endogenous growth, establishing that "human capital is accumulated through schooling and... the rate of human capital accumulation, not the level, determines the long-run growth rate." Romer (1990) pushed further, specifying in "Endogenous Technological Change" that it is the *stock* of human capital that determines the long-run rate of technological change and hence per capita income growth — not labour force size alone.

For India specifically, the distinction between demographic structure and demographic quality is the central analytical tension of the study. India's demographic size creates a large numerator of labour supply, but the *productivity* of that supply — shaped by nutrition, literacy, health-seeking behaviour, cognitive skills, and years of completed schooling — remains far below East Asian counterparts despite a comparable fertility transition. The DQI measures this quality gap across 10 carefully selected, annually available, and theoretically grounded variables spanning health quality, nutritional adequacy, educational attainment, and skills formation.

The DQI's conceptual mandate is also bounded by a critical endogeneity constraint. In the OLS regression model, the DQI must be an *input* to economic growth — a cause, not a consequence. Every variable in the DQI was selected on the basis that it measures a stock or flow of human capital that is determined by investments made years or decades earlier, not by the current year's economic performance. The causal arrow must run from DQI to EGI, not the reverse.

6.2 The Ten Variables of the DQI: Structure and Sub-Dimensions

The DQI aggregates ten annual time-series variables for India from 2000 to 2024, spanning four sub-domains of human capital quality: longevity and health system reach, nutritional capital, educational attainment, and skills formation.

Table 5 DQI Variables, the sub dimensions and direction of the variables

Variable	Sub-Domain	Direction
Life expectancy at birth, total (years)	Longevity / Health Quality	Higher = better
Mean years education of adults aged 20+	Educational Attainment Stock	Higher = better
Prevalence of stunting, height for age (modeled estimate, % of children under 5)	Nutritional Capital	Lower = better (inverted)
Immunization, DPT (% of children ages 12–23 months)	Health System Reach	Higher = better
Literacy rate, adult total (% of people ages 15 and above)	Foundational Educational Quality	Higher = better
Maternal mortality ratio (modeled estimate, per 100,000 live births)	Women's Health Quality	Lower = better (inverted)
Mortality rate, under-5 (per 1,000 live births)	Child Health Capital	Lower = better (inverted)
School enrollment, secondary (% gross)	Education Accumulation Flow	Higher = better
School enrollment, tertiary (% gross)	Higher Education / Innovation Capital	Higher = better
Vocational and Technical enrolment (% of total secondary enrolment), total	Skills Formation	Higher = better

Variables marked as "inverted" undergo the direction-alignment transformation $x' = \max(x_i) + \min(x_i) - x_{it}$ before normalisation, ensuring that higher composite scores consistently reflect better demographic quality.

6.3 Variable-by-Variable Literature Review

6.3.1 Life Expectancy at Birth, Total (Years)

Life expectancy at birth (LEB) is one of the most fundamental and widely studied measures of population health quality. It is defined as the average number of years a newborn would be expected to live if the age-specific death rates prevailing in the year of birth remained constant throughout the individual's lifetime. It is not an average age at death of the currently living population — it is a forward-looking hypothetical derived from the current period's mortality experience across all age groups using life-table methodology.

The inclusion of LEB in the DQI rests on its role as the aggregate outcome of the health system's capacity to maintain and extend productive life. Bloom and Canning (2000), in their landmark *Science* paper "The Health and Wealth of Nations," demonstrated that "workers who are healthier are more productive, earn higher wages, and can save more for old age" — establishing a clean causal channel from health capital, summarised by LEB, to economic performance. Their study found that even after controlling for education, investment, and institutions, a 5-year increase in life expectancy raised economic growth by 0.3–0.5 percentage points per year. Deaton (2003), in "Health, Inequality, and Economic Development," provides the fullest theoretical account: LEB is the summary outcome of a society's cumulative health investments — nutrition, sanitation, immunisation, curative care — all of which shape the productive life of the workforce.

India's LEB rose from 62.75 years in 2000 to 72.24 years in 2024 — an increase of almost 10 years of average life in 24 years. The COVID-19 pandemic reversed this progress in 2021, when LEB fell sharply to 67.3 years before recovering to 71.7 in 2022 and 72.0 in 2023. This reversal and recovery are captured in the DQI composite and represent the index's sensitivity to genuine health shocks — exactly as intended.

6.3.2 Mean Years Education of Adults Aged 20+

Mean years of schooling (MYS) for adults aged 20 and above measures the average number of years of formal education that the adult population has accumulated. It is the stock dimension of educational quality: not the current flow of students entering school, but the accumulated educational capital of the entire adult population currently available to the labour market.

Lucas (1988) explicitly places human capital — indexed by the stock of acquired education — at the centre of endogenous growth: "human capital is accumulated through schooling and... the rate of human capital accumulation, not the level, determines the long-run growth rate." Barro and Lee (2013), in their comprehensive

cross-country dataset of educational attainment covering 146 countries, establish MYS as the standard measurable proxy for the human capital stock, derived by multiplying the population's educational attainment distribution by standard years-of-schooling durations. Mankiw, Romer, and Weil (1992) found that adding human capital (measured by education rates) to the Solow model nearly doubles its explanatory power for cross-country income differences, confirming that MYS-type variables are the most important structural determinants of long-run growth. Hanushek and Woessmann (2008) nuance this, finding that it is cognitive skills — not mere years of schooling — that are "powerfully related to individual earnings, to the distribution of income, and to economic growth," but acknowledge that MYS remains the primary observable proxy for the educational capital stock.

India's MYS for adults aged 20+ rose from 4.14 years in 2000 to 6.88 years in 2023, an improvement of 2.74 years of average adult education in 23 years. The endogeneity firewall is strong: a person aged 30 in 2020 completed their schooling between 2003 and 2010, making their MYS contribution predetermined with respect to 2020 GDP growth. The current year's economic performance cannot alter past schooling decisions.

6.3.3 Prevalence of Stunting, Height for Age (Modelled Estimate, % of Children Under 5)

Stunting is the permanent, largely irreversible failure of physical and cognitive growth caused by chronic malnutrition during the first 1,000 days of life — from conception to a child's second birthday. A child is classified as stunted when their height-for-age z-score falls more than two standard deviations below the WHO Child Growth Standards reference population median. Stunting is not merely a health indicator — it is a measure of destroyed human capital. Stunted children grow into adults with permanently reduced cognitive capacity, lower physical stamina, shorter productive lifespans, and reduced earnings potential. In this sense, stunting prevalence is the negative accumulation of human capital — the anti-investment in the DQI's quality stock.

Schultz (1961) argued that nutritional investment is one of the five canonical forms of human capital formation: "expenditures on health and nutrition that raise the productive capacity of workers." Malnutrition — which stunting measures directly — destroys this investment by impairing the cognitive and physical substrate on which all subsequent educational capital accumulates. Research published in *JAMA Network Open* (2023) confirmed that "economic growth was weakly associated with childhood malnutrition and several contributing factors" — precisely because nutritional outcomes depend on the distribution of income (through food prices, agricultural wages, and social protection), not on aggregate GDP — establishing that stunting is

structurally independent of contemporaneous growth and belongs on the *input* side of the growth equation.

India's stunting prevalence declined from approximately 50% of children under 5 in 2000 to 32.8% in 2023, according to the modelled estimates in the dataset — still among the highest in the world, and a persistent marker of India's deepest quality deficit. The data for inter-survey years are modelled estimates interpolated between NFHS rounds (2005–06, 2015–16, 2019–21), and are inverted in the index construction so that a lower prevalence produces a higher DQI contribution.

6.3.4 Immunization, DPT (% of Children Ages 12–23 Months)

DPT immunisation coverage measures the percentage of children aged 12–23 months who have received all three recommended doses of the diphtheria-pertussis-tetanus vaccine. It is used here as the primary proxy for the *health system's reach* into the population — the degree to which India's public health infrastructure is successfully delivering preventive interventions to the most vulnerable age cohort. Full immunisation prevents vaccine-preventable diseases that cause developmental delays, school absenteeism, and premature mortality, all of which degrade long-run human capital quality.

Grossman (1972), in his foundational paper "On the Concept of Health Capital and the Demand for Health," frames health as "a durable capital stock that yields an output of healthy time," and notes that "individuals inherit an initial amount of this stock that depreciates with age and can be increased by investment." Immunisation is precisely such an investment — it augments the child's health capital stock by preventing depletions through infectious disease. Bloom and Canning (2000) explicitly note that health improvements "operate through reduced illness and improved cognitive function, with lags of 10–20 years before the full productivity effect is realised" — confirming that immunisation coverage is an input variable with long-lagged effects, not a contemporaneous economic outcome. The Mission Indra Dhanush campaign launched in 2014 produced measurable DPT coverage gains in 2016–2018, with a 2–4 year lag between campaign investment and survey-measured outcome — confirming the temporal pre-determination.

India's DPT immunisation coverage rose from 58% in 2000 to 94% in 2024 — a dramatic expansion of the health system's reach, reflecting successive immunisation campaigns, ASHA network expansion, and cold-chain improvements. The COVID-19 disruption is visible: coverage dipped from 91% in 2019 to 85% in 2020 and 2021 before recovering to 93% in 2022.

6.3.5 Literacy Rate, Adult Total (% of People Ages 15 and above)

The adult literacy rate is the percentage of the population aged 15 and above who can both read and write — with understanding — a short simple statement about everyday life in any language. It is the foundational threshold of human capital: the prerequisite for all further educational accumulation, for engaging with written instructions, for accessing formal financial services, and for transmitting knowledge to children. An economy where a large fraction of the adult workforce is illiterate is structurally constrained in its capacity to adopt new technologies, absorb training, or participate in the formal economy.

Schultz (1961) identifies literacy as the most basic output of educational investment — "direct expenditures on education... are clear examples" of human capital investment, with literacy as the minimum threshold output. Mincer (1974), in his foundational work on earnings functions, establishes that years of schooling — with literacy as the entry-level return — are the primary determinant of individual earnings capacity and therefore of aggregate labour productivity. Convergence analyses of regional literacy rates in India confirm that literacy dynamics follow long-run demographic and educational policy cycles — driven by historical schooling investments, family planning outcomes (fewer children enabling more per-child educational investment), and state-level policy — rather than business cycle fluctuations.

India's adult literacy rate was 61.0% in 2001 (Census), rising to approximately 74% in 2011 (Census) and reaching approximately 81.7% by 2023 in this dataset — a continuous structural improvement, though with significant data gaps requiring OLS imputation for intercensal years. The endogeneity firewall: a person aged 40 in 2020 who is literate became literate either through schooling in the 1980s or through a literacy campaign in the 1990s — neither of which was caused by 2020 GDP growth.

6.3.6 Maternal Mortality Ratio (Modelled Estimate, per 100,000 Live Births)

The Maternal Mortality Ratio (MMR) measures the number of maternal deaths "deaths of women during pregnancy, childbirth, or within 42 days of delivery from pregnancy-related causes, per 100,000 live births". It is perhaps the most sensitive indicator of women's access to quality reproductive healthcare, simultaneously capturing three dimensions of demographic quality: women's nutritional and health status before pregnancy, the quality and accessibility of antenatal care, and the skill and infrastructure of the health system at the moment of delivery. In the DQI, the MMR is inverted — a lower MMR yields a higher DQI score — reflecting the direction: less maternal mortality means better quality of women's health capital.

Grossman (1972) writes that "more educated people are more efficient producers of health," establishing that education and health quality are jointly determined inputs to human capital formation. The maternal mortality ratio directly measures the health system's capacity to protect women's productive and reproductive capital — the loss of a young mother is simultaneously a human capital destruction event for the family, the community, and the economy. Bloom and Canning (2000) confirm that maternal health improvements are among the highest-return health investments precisely because they protect not just the mother's human capital but also her children's early developmental environment. National Health Mission guidelines explicitly frame MMR as "a key indicator of healthcare quality and accessibility" — an input quality measure of the health system, not an economic outcome.

India's MMR fell from 362 per 100,000 live births in 2000 to 87 in 2024 - a reduction of 76% in 24 years, reflecting institutional delivery rate expansion, ASHA worker deployment, and antenatal care coverage improvements. The COVID disruption is visible: the 2021 value rises to 155, before recovering to 90 in 2022 and falling further to 80 in 2023.

6.3.7 Mortality Rate, Under-5 (per 1,000 Live Births)

The under-five mortality rate (U5MR) is the probability — expressed per 1,000 live births - that a child born in a given year will die before reaching their fifth birthday. It is the single most widely used composite indicator of child health quality in the demographic and public health literature because it aggregates mortality risks across the neonatal period, infancy, and early childhood — all of which respond to different but interrelated dimensions of demographic quality: nutritional adequacy, immunisation coverage, access to oral rehydration therapy, household sanitation, and maternal education. In the DQI, the U5MR is inverted — a lower rate means better health capital.

Grossman (1972) describes health as "a durable capital stock that yields an output of healthy time" and notes that the stock "can be increased by investment." The U5MR inversely measures how well India's health capital stock is being maintained through the critical first five years of life — making it a genuine quality input measure. IGME (UN Inter-agency Group for Child Mortality Estimation) documentation confirms that U5MR responds to "health interventions and social drivers rather than contemporaneous economic fluctuations," including vaccination missions, nutritional programmes (ICDS), and sanitation infrastructure (Swachh Bharat) — all multi-year, pre-determined public investments.

India's U5MR declined from 91.8 per 1,000 live births in 2000 to 26.6 in 2024 — a 71% reduction, one of the most dramatic improvements in child survival globally over

this period. The 2021 COVID disruption causes a visible spike in mortality, temporarily reversing the trend before recovery in 2022.

6.3.8 School Enrollment, Secondary (% Gross)

The Gross Enrolment Ratio at the secondary level (GER-Secondary) is the total number of students enrolled in secondary education — Classes 9–12 in India -divided by the official secondary-school-age population (approximately 14–17 years), expressed as a percentage. It is the *flow* dimension of educational quality: the rate at which India is currently channelling its young population into secondary-level human capital formation. While Mean Years of Schooling (Variable 2) measures the *stock* of accumulated educational capital in the adult workforce, GER-Secondary measures the *current rate of stock accumulation* among the school-going cohort.

Romer (1990) is explicit that it is the stock of human capital that "determines the rate of technological change, and hence the long-run growth rate of per capita income" — and GER-Secondary is the primary mechanism by which that stock is built. Azariadis and Drazen (1990), in "Threshold Externalities in Economic Development," argued that "rapid growth cannot occur without relatively overqualified labor" — establishing secondary enrolment as a prerequisite *input* condition for growth acceleration, not a consequence. Mincer (1974) documented that the earnings returns to secondary education are significantly higher than to primary education, validating the secondary level as a structurally important threshold in the human capital accumulation ladder.

India's GER-Secondary rose from 47.2% in 2000 to approximately 78.1% in 2024 — a dramatic expansion of secondary access, though still below East Asian comparator levels. Current GDP growth cannot raise this year's GER-Secondary in any contemporaneous sense: school infrastructure has been built or not built, teachers trained or not, and enrolment decisions for the current academic year were made months before GDP growth rates are even computed.

6.3.9 School Enrollment, Tertiary (% Gross)

Tertiary enrolment covers all students enrolled in post-secondary education — colleges, universities, technical institutes, and polytechnics — as a percentage of the official tertiary-age population (approximately 18–23 years). It measures India's investment in the highest tier of human capital formation: the production of graduates, researchers, engineers, and skilled professionals who drive innovation, technology adoption, and productivity at the knowledge frontier.

Romer (1990) placed tertiary human capital at the very centre of endogenous growth: in his model, it is the stock of tertiary-educated researchers and innovators that generates technological change, which is the only source of sustained long-run per capita income growth. Hanushek and Woessmann (2008) found that cognitive skills

— predominantly developed through tertiary education — are "powerfully related to individual earnings, to the distribution of income, and to economic growth," supporting tertiary enrolment as a high-priority DQI component. Bloom, Canning, and Sevilla (2003) extended the demographic dividend hypothesis to include higher education: "the demographic dividend provides the opportunity for investment in tertiary education, which in turn raises human capital quality and growth — but only if the enrolment infrastructure is built in time."

India's tertiary GER rose from just 9.9% in 2000 to 34.4% in 2024 — a threefold expansion, though still well below the OECD average of approximately 70–80%. This rapid but late expansion of tertiary access is one of the most consequential quality improvements in the DQI dataset, reflecting the post-2005 expansion of private engineering colleges, deemed universities, and government schemes such as the Rashtriya Uchchatar Shiksha Abhiyan (RUSA).

6.3.10 Vocational and Technical Enrolment (% of Total Secondary Enrolment)

Vocational and Technical Education and Training (TVET) enrolment measures the share of secondary-level students who are enrolled in vocational or technical streams — as opposed to the general academic stream — expressed as a percentage of total secondary enrolment. This variable captures the *skills formation* dimension of demographic quality: the degree to which India is producing job-ready, technically skilled graduates capable of entering the industrial and services workforce without further training.

The theoretical case for TVET as a human capital quality variable runs through the endogenous growth literature's distinction between general and specific human capital. Mincer (1974) documented that firm-specific and occupation-specific skills — precisely what TVET provides — generate the highest wage premiums for workers at the margin, because they directly address the gap between what the general school system provides and what employers need. Majumder (2013), in a study of India's skill gap, found that "the mismatch between the skills provided by the general education system and those required by employers" is the primary reason for India's low labour productivity despite rising educational attainment — making TVET enrolment the metric that directly captures the solution to this mismatch. Marois, Gietel-Basten, and Lutz (2021), in their demographic analysis of India's workforce quality, stress that "fixing skill gaps and boosting female labour force participation" are the two most critical interventions for converting demographic structure into development outcomes.

India's TVET enrolment as a share of secondary enrolment was extremely low throughout most of the study period — hovering at approximately 0.7–1.4% from 2000 to 2019, far below comparator economies like Germany (40–50%) or China (30–40%). The COVID period shows an anomalous spike in 2020 (3.1%), 2021 (4.6%), and 2022 (3.5%), potentially reflecting reclassification or methodological changes in UDISE+ data rather than genuine enrolment growth. This persistent structural gap in skills formation is one of the DQI's most diagnostic readings of India's quality deficit.

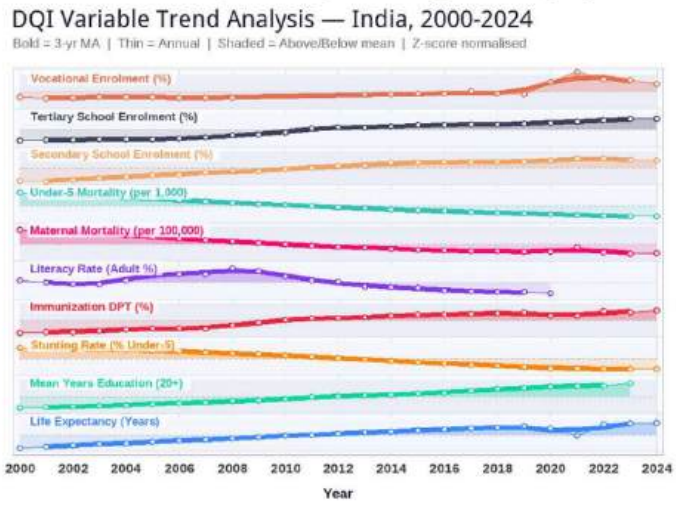


Figure 5 DQI variables Trend Analysis (2000 – 2024)

6.4 What the DQI Composite Signal Tells Us

The DQI composite score synthesises these ten dimensions of human capital quality into a single annual index that answers the question: how much human capital quality did India's population embody in this year? A high DQI score means that India's life expectancy was above its long-run average, fewer children were stunted, immunisation coverage was strong, adults were more literate, maternal and child mortality were low, more students were in secondary and tertiary education, and TVET participation was rising — all simultaneously. The geometric mean's partial non-compensability ensures that persistent weakness on any one dimension — such as the stubbornly low TVET enrolment or the high stunting prevalence in early years — is not concealed by strengths elsewhere.

In the regression model, the DQI coefficient measures whether years of better human capital quality correlate with years of better comprehensive economic growth performance (EGI). The theoretical expectation — grounded in Schultz (1961), Lucas (1988), Bloom and Canning (2000), and Hanushek and Woessmann (2008) — is a positive and statistically significant coefficient. However, the study's central intellectual contribution lies in comparing the DQI's coefficient against the DSI's: if the DSI (demographic structure) shows a positive coefficient but the DQI (demographic quality) is weak or negative, it would constitute evidence that India's dividend is primarily a *structural* phenomenon — numbers without quality — rather than a genuine transformation of human capital.

6.5 Descriptive Overview of the DQI Trajectory

India's DQI score grew from 1.36 in 2000 to 4.36 in 2023, with a mean of 2.90 and a median of 3.04 — a slower and more gradual trajectory than the DSI, reflecting the structural reality that human capital quality takes decades to build. The annual improvement rate of +0.13 points per year is the slowest among all five independent indices, consistent with the literature's emphasis on the generational timescales of health and education investment payoffs. The COVID-19 shock of 2020–2021 is clearly visible as a disruption: LEB falls, U5MR deteriorates, DPT coverage dips, and MMR spikes — all captured in the composite and producing a notch in the otherwise steady upward trajectory. The recovery by 2022–2023 demonstrates the index's responsiveness to both deterioration and repair of health capital.

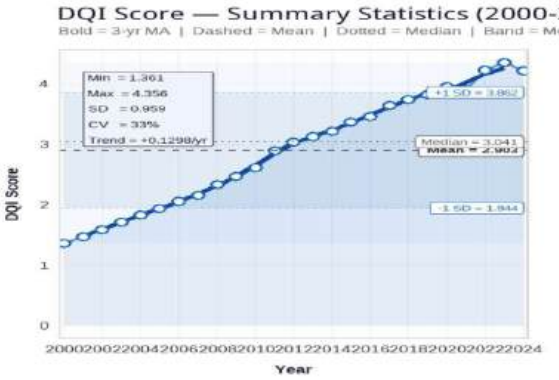


Figure 6 DQI Descriptive Statistics (2000 – 2024)

The coefficient of variation of the DQI across the 25-year sample is low — reflecting stable, trend-dominated movement rather than cyclical volatility. This makes the DQI

theoretically appropriate as a structural regressor: it captures the slow, cumulative improvement in India's human capital quality, not the business cycle.

6.6 Data Sources

All ten DQI variables are drawn from the following primary sources:

- **World Bank World Development Indicators (WDI)**: Primary source for life expectancy, DPT immunisation, adult literacy rate, maternal mortality ratio , under-5 mortality rate, secondary GER, and tertiary GER.
- **UNESCO Institute for Statistics (UIS)**: Primary source for mean years of schooling, GER-Secondary cross-validation.
- **National Family Health Survey (NFHS) Rounds 3, 4, 5** (IIPS/ICF): Primary source for stunting prevalence (HAZ < −2 SD), DPT coverage cross-validation, and MMR supplementary estimates for survey years 2005–06, 2015–16, and 2019–21.
- **Sample Registration System (SRS)**: Cross-validation source for LEB and U5MR through abridged life tables; primary source for MMR via the SRS Special Bulletin on Maternal Mortality.
- **ASER Centre / Pratham Foundation**: Source for learning outcomes data (ASER Grade 5 reading proficiency), used as a supplementary indicator and for contextualisation of the literacy and secondary enrolment trends.
- **MoSPI UDISE+**: Annual school enrolment data at secondary level for cross-validation of GER-Secondary and TVET enrolment shares.

6.7 Variable Selection Logic and Exclusions

Following OECD Handbook Step 2 discipline, the final ten DQI variables were selected from a longlist of approximately 40 candidate human capital quality indicators across five sub-domains (health, nutrition, education, labour, and gender-social quality). The key exclusion decisions are as follows.

Healthy Life Expectancy (HALE) versus Life Expectancy at Birth (LEB): HALE was considered as a more refined alternative to LEB, adjusting for years lived in disability. It was excluded because continuous annual national-level HALE estimates for India from 2000 to 2024 are not available from any primary source — only quinquennial GBD estimates exist. LEB is available annually from the SRS and WDI and provides sufficient information content.

Under-5 Mortality Rate (U5MR) versus Infant Mortality Rate (IMR): The IMR is already used in the DSI as a demographic *structural* variable — specifically as the child-survival hypothesis variable that drives the fertility transition. The U5MR is included in the DQI as a health *quality* variable because it spans a broader developmental window (0–4 years) and aggregates neonatal, infant, and early childhood mortality into a single composite health capital measure. The two variables are theoretically and functionally distinct in this framework.

ASER Learning Outcomes Rate (Grade 5 reading proficiency): The ASER Rate was fully justified as a DQI variable — and is one of the strongest quality variables by theoretical grounding (Hanushek and Woessmann, 2008) — but was excluded from the *final* DQI composite because the annual series is only available from 2005 onwards (ASER was launched in 2005), creating missing values for 2000–2004 that would disproportionately affect the composite scores for the early sample period. It remains available as a supplementary indicator for contextualisation and robustness checks.

Female Labour Force Participation Rate (FLFPR): FLFPR was justified in the DQI reference document as a proxy for women's agency and quality, consistent with Sen's (1999) capability approach. However, the India FLFPR data exhibits the well-documented U-shaped pattern — declining from 2000 to 2017 then recovering sharply — which creates a non-monotonic structural break in the time series. This structural anomaly was judged to introduce more noise than signal into the composite, and FLFPR was instead reserved for the HCI (Harnessing Capacity Index), where its labour market activation interpretation is more directly relevant.

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Disability-Adjusted Life Years (DALYs): DALYs were considered as a comprehensive health burden variable. They were excluded due to lack of continuous annual national-level series — GBD estimates are available for benchmark years only, requiring heavy interpolation that would introduce methodological uncertainty disproportionate to the variable's marginal analytical contribution.

These exclusions confirm the OECD Handbook's principle of selecting variables based on analytical soundness, annual availability, and non-redundancy — ensuring the DQI composite is both statistically clean and theoretically rigorous.

6.8 The DQI in the Regression Framework: Theoretical Expectations and the India Paradox

In the regression model, the DQI enters as the human capital quality regressor — the variable that tests whether the *productivity* of India's growing working-age population kept pace with its *size*. The expected sign of the DQI coefficient is positive: years with better health, education, and nutritional quality should produce better comprehensive

economic outcomes. This expectation is grounded in three decades of human capital growth theory: Schultz (1961) on investment in human capital, Lucas (1988) on the centrality of the human capital stock to endogenous growth, Bloom and Canning (2000) on health's direct effect on economic growth, and Hanushek and Woessmann (2008) on cognitive skills as the true driver of long-run development.

However, the DQI is simultaneously where the study's most important empirical question is most sharply posed. The literature on India's growth experience raises the persistent concern articulated most clearly by Drèze and Sen (2013) in *An Uncertain Glory* that India's remarkable GDP growth since 2000 has been achieved *alongside* and not *because of* improvements in human development. If the DQI's coefficient in the regression is unexpectedly small, or if the DQI's improvement trajectory lags the DSI's structural expansion, the data would speak directly to this concern: India has accumulated demographic structure far faster than it has accumulated demographic quality.

The DQI is therefore not merely a second independent variable. It is the analytical partner of the DSI the quality mirror of the quantity story. Together, the DSI and DQI operationalise the central research question of this study: has India successfully converted its demographic dividend window into a genuine human capital transformation, or has the structural potential of the dividend remained unrealised because the quality of the working-age population has not kept pace with its expanding size?

Chapter 7
The Harnessing Capacity Index (HCI)

7.1 Conceptual Foundation: What the HCI Measures and Why it matters?

The Harnessing Capacity Index (HCI) is the third independent variable in the regression model, and it occupies the most analytically distinctive space in the entire five-index framework. The DSI (Chapter 5) measures how many working-age people India has. The DQI (Chapter 6) measures how healthy, educated, and skilled those people are. The HCI asks the third and logically subsequent question: how much of that available, quality-endowed working-age population is India actually mobilising into productive employment? A country may have a large, well-educated working-age cohort and still fail to harness it if women are culturally excluded from the labour force, if growth is jobless, if employment remains trapped in low-productivity agriculture, or if the economy generates vulnerable informal work rather than formal salaried employment. The HCI is designed to measure this gap between demographic potential and actual labour market activation.

This conceptual positioning is both the HCI's greatest strength and its most challenging methodological constraint. The intermediate space the HCI occupies — between human capital endowment (DQI) and economic output (EGI) — is precisely the space where India's demographic dividend debate is most contested. Bloom and Williamson (1998) demonstrated that structural advantage (captured by DSI) drives growth, but only through the mechanism of labour supply expansion. Marois, Gietel-Basten, and Lutz (2021) showed that the dividend's realisation depends critically on "fixing skill gaps and boosting female labour force participation" — the exact dimensions the HCI captures. The empirical puzzle of why India's fastest growth decade (2004–05 to 2011–12) coincided with declining employment absorption — what Mehrotra, Parida, Sinha, and Gandhi (2014) termed "jobless growth" — is the central problem the HCI is built to measure.

The theoretical foundation of the HCI draws from three intellectual traditions. First, the Lewis (1954) dual-sector model, which posits that development proceeds through the reallocation of labour from low-productivity subsistence agriculture into high-productivity industrial and services sectors — establishing the non-agricultural employment share and structural transformation as the core mechanism of labour capacity harnessing. Second, the classical labour supply literature of Mincer (1974), which establishes how participation decisions are driven by wages, reservation wages,

and opportunity costs rather than contemporaneous GDP levels. Third, the structural transformation literature of Fields (2011) and Ghose, Majid, and Ernst (2008), which examines how the composition and quality of employment evolve with development — grounding variables like formality, labour productivity, and employment elasticity as institutional and structural determinants rather than cyclical outcomes.

7.2 The Ten Variables of the HCI: Structure and Sub-Dimensions

The HCI aggregates ten annual time-series variables for India from 2000 to 2024, drawn from the ILO modelled estimates (ILOSTAT) and cross-validated against the Periodic Labour Force Survey (PLFS) and India KLEMS. The ten variables span five analytically distinct sub-domains of labour capacity utilisation.

Table 6 HCI Variables, the sub dimensions and direction of the variables

Variable	Sub-Domain	Direction
Labor force participation rate, total (% of total population ages 15+)	Supply-Side Activation	Higher = better
Employment to population ratio, 15+, total (%)	Employment Absorption	Higher = better
Wage and salaried workers, total (% of total employment)	Employment Quality / Formalisation	Higher = better
Vulnerable employment, total (% of total employment)	Precariousness / Informality	Lower = better (inverted)
GDP per person employed (constant 2021 PPP $)	Labour Productivity	Higher = better
Employment Elasticity of Output	Growth-to-Jobs Conversion	Higher = better
Employment in agriculture (% of total employment)	Structural Transformation	Lower = better (inverted)
Employment in industry (% of total employment)	Structural Upgrade	Higher = better
Unemployment, youth total (% of total labor force ages 15–24)	Youth Capacity Wastage	Lower = better (inverted)
Share of youth not in education, employment or training, total (% of youth population)	NEET — Total Disengagement	Lower = better (inverted)

Variables marked as "inverted" undergo the direction-alignment transformation $x' = \max(x_i) + \min(x_i) - x_{it}$ before normalisation, ensuring that higher composite scores consistently reflect better labour capacity harnessing.

7.3 Variable-by-Variable Literature Review

7.3.1 Labor Force Participation Rate, Total (% of Total Population Ages 15+)

The Total Labour Force Participation Rate (LFPR) is the proportion of the working-age population (aged 15 and above) that is either currently employed or actively seeking employment. It is the foundational supply-side activation measure of the HCI the variable that answers whether India's demographically expanding working-age cohort is choosing to enter the economic sphere at all.

Lewis (1954), in his foundational "Economic Development with Unlimited Supplies of Labour," established that the transition of developing economies from stagnation to growth is contingent on labour supply mobilisation from the subsistence sector. Mincer (1974) formalised the individual participation decision: workers enter the labour force when the market wage exceeds their reservation wage — the shadow price of household time — making the LFPR a structural outcome of wages, non-labour income, cultural norms, and educational enrolment decisions accumulated over years. Mehrotra, Parida, Sinha, and Gandhi (2014) documented that India's LFPR decline between 2004–05 and 2011–12 "was not driven by falling wages or declining economic activity, but by a combination of the income effect of rising rural non-farm wages and the pull of secondary and higher education enrolment, both of which are structural and slow-moving phenomena" — establishing directly that LFPR is causally prior to GDP growth, not a consequence of it.

India's total LFPR in this dataset declined from 60.1% in 2000 to a trough of 51.5% in 2020, before recovering to 55.6% in 2024. This U-shaped trajectory — decades of declining participation followed by a post-2019 recovery driven by rural female re-entry — is one of the most diagnostic structural signals in the entire HCI dataset, reflecting the negative income effect documented by Mehrotra et al. (2017) in the decline phase and MGNREGS-facilitated rural re-mobilisation in the recovery phase.

7.3.2 Employment to Population Ratio, 15+, Total (%) (Modelled ILO Estimate)

The Employment-to-Population Ratio (EPR) measures the percentage of the working-age population (aged 15 and above) that is actually employed — the hard absorption measure that complements the LFPR's supply-side indicator. While the LFPR tells how many people want to work, the EPR tells how many are actually working. The gap between the two is the unemployment rate. In development economics, the EPR is the most direct observable measure of whether an economy is successfully harnessing its demographic capacity into productive activity.

Mehrotra et al. (2014) found that during India's highest GDP growth phase (2004–05 to 2011–12), the EPR actually declined by several percentage points "for the first time since Independence, the absolute number of workers declined significantly" — demonstrating that EPR can move counter to GDP, validating it as an independent structural variable in the OLS framework. Kannan and Raveendran (2009) documented that India's employment crisis is fundamentally about the EPR, not unemployment: people exit the labour force entirely rather than registering as unemployed, making the EPR a more truthful measure of employment absorption than the unemployment rate alone.

India's EPR fell from 55.5% in 2000 to a low of 47.5% in 2020 before recovering to 53.3% in 2024. The COVID-19 shock of 2020 produced the deepest single-year EPR drop in the dataset — from 48.9% in 2019 to 47.5% in 2020 before recovering sharply in 2021–2022, reflecting the structural resilience of India's informal labour market to aggregate GDP shocks.

7.3.3 Wage and Salaried Workers, Total (% of Total Employment) (Modelled ILO Estimate)

The wage and salaried employment share measures the percentage of India's total employed workforce holding a regular wage or salaried job meaning they have a defined employer who pays them a fixed wage or salary, as opposed to being self-employed or casual daily-wage labourers. It is the formalisation dimension of employment quality: the fraction of the workforce with an employer, a regular pay cheque, and at least some institutional recognition of the employment relationship.

Besley and Burgess (2004), in "Can Labor Regulation Hinder Economic Performance? Evidence from India," demonstrated that formal salaried employment creation is determined primarily by labour regulation frameworks — specifically, the Industrial Disputes Act and Contract Labour Act — not by the growth rate itself: "states which amended the Industrial Disputes Act in a pro-worker direction experienced lowered output, employment, investment, and productivity in registered manufacturing." This finding establishes that the salaried employment share is an institutional variable, pre-determined by regulatory architecture. Hussmanns (2004) confirms that the distinction between wage employment and self-employment is the primary operationalisation of the formal-informal boundary in developing country labour markets, making this variable the most direct proxy for India's structural formalisation trajectory.

India's wage and salaried employment share rose from 15.3% in 2000 to 24.6% in 2024 — a historically significant but still modest increase, with three-quarters of the workforce remaining in non-salaried employment even at the end of the sample period. This persistent structural constraint on formalisation is one of the HCI's most diagnostic structural weaknesses in the India story.

7.3.4 Vulnerable Employment, Total (% of Total Employment) (Modelled ILO Estimate)

Vulnerable employment is defined as the sum of own-account workers (the self-employed with no employees) and contributing family workers — those whose employment status is characterised by inadequate earnings, low productivity, and difficult conditions of work. The ILO treats vulnerable employment as the operational measure of precarious, unprotected labour that lacks formal contracts, social security, and statutory employment protections. In the HCI, it is inverted: a lower vulnerable employment share contributes a higher HCI score.

Fields (2011) described informality in developing countries as "a structural feature reflecting missing markets, weak institutions, and low capital intensity" — not a cyclical response to income changes — establishing vulnerable employment as a structural-institutional variable that evolves over decades, not quarters. The NCEUS (2009) — the National Commission for Enterprises in the Unorganised Sector — documented that approximately 92% of India's workforce was informally employed in the mid-2000s, and identified the structural drivers as the coverage thresholds of EPF and ESI legislation, not GDP fluctuations. The ILO Statistical Update confirms that in India (2004/2005), "83.5 percent of all employment was in the informal sector" — establishing both the severity of the problem and its institutional-structural determination.

India's vulnerable employment share declined from 83.7% in 2000 to 72.1% in 2024 — a structural improvement of 11.6 percentage points — but the pace is strikingly slow: a quarter-century of labour market evolution reduced vulnerability by only about 0.5 percentage points per year. This slow secular decline, against the backdrop of rapid GDP growth, is one of the most important structural findings in the entire study — the HCI's vulnerable employment variable directly captures India's persistent failure to convert economic growth into formal, protected employment relationships.

7.3.5 GDP per Person Employed (Constant 2021 PPP $) - Labour Productivity

GDP per person employed measures the real economic output generated per employed worker, expressed in constant 2021 PPP-adjusted international dollars to ensure comparability across years. It is the productivity dimension of labour capacity harnessing — not merely how many people are working, but how intensively and efficiently each employed person is generating economic value. Two economies with identical EPRs may have very different HCI scores if one's workers produce twice as much per hour as the other's.

In the Solow (1956) growth framework, labour productivity — output per worker — is the primary channel through which capital deepening and total factor productivity

improvements translate into higher per capita income. India KLEMS (2024) explicitly presents labour productivity as an explanatory rather than explained variable, decomposing GVA growth into employment growth and productivity improvement components. Ghose, Majid, and Ernst (2008) confirm that "productivity growth in developing economies is primarily driven by capital deepening and technology adoption — both of which are determined by investment decisions made in prior years, not by contemporaneous output growth" — establishing that the current year's labour productivity reflects investment decisions made 3–10 years earlier, making it pre-determined relative to the contemporaneous EGI.

India's GDP per person employed rose dramatically from $8,662 (constant 2021 PPP) in 2000 to $24,430 in 2024 — nearly a threefold increase in real labour productivity over 24 years. Yet the 2020 COVID disruption produced a visible dip ($22,174 in 2019 to $21,152 in 2020) before recovery, confirming the variable's sensitivity to genuine macroeconomic shocks while maintaining its structural trend character.

7.3.6 Employment Elasticity of Output

The Employment Elasticity of Output measures how many percentage points of employment growth are generated for every one percentage point of GDP growth — a "job multiplier per unit of growth" ratio. An elasticity of 0.50 means each 1% of GDP growth generates 0.50% employment growth; an elasticity of 0.10 signals near-jobless growth. For the HCI, a higher elasticity means the economy is more efficiently converting its growth momentum into actual jobs — a direct measure of capacity-harnessing efficiency in the growth-to-employment transmission channel.

The RBI (2009) study on employment elasticity in India found that aggregate elasticity declined from approximately 0.44 in the 1980s to "0.18 to 0.20 during the post reform period" — signalling a structural shift toward capital-intensive, employment-light growth. The World Bank (2024) confirms that "employment elasticities of growth vary significantly across countries and sectors, but are in most cases below 1.0, implying that employment grows less than GDP due to increasing productivity" — validating the variable as a structural coefficient. Besley and Burgess (2004) show that employment elasticity in Indian states was determined by industrial relations legislation rather than growth rates, establishing its institutional-structural determination.

India's employment elasticity in this dataset shows the high volatility expected of a derived ratio — ranging from near zero in the 2006–2010 "jobless growth" period to 0.80 in 2000 and 0.68 in 2022 and 2019. The three-year trailing average used in the composite smooths this volatility, extracting the structural signal from the cyclical noise. The persistently low elasticities of the 2000s — averaging approximately 0.2 —

are precisely the quantitative expression of the "jobless growth" paradox that the HCI is designed to capture.

7.3.7 Employment in Agriculture (% of Total Employment)

The agricultural employment share measures the percentage of India's total employed workforce engaged in agriculture, forestry, and fishing. In the HCI, this variable is inverted: a higher agricultural share means more workers are trapped in the low-productivity sector, which is a less favourable harnessing outcome. This variable is the most direct observable measure of Lewis's (1954) structural transformation: the defining feature of development is the movement of workers from subsistence agriculture into more productive industrial and services activities.

Lewis (1954) built his entire model of economic development around this variable: "in countries where the supply of labour is unlimited... development consists of the transfer of workers from low-productivity agricultural activities to high-productivity capitalist activities." Mehrotra et al. (2014) documented that between 2004–05 and 2011–12, agricultural employment contracted by 37 million workers as mechanisation and construction growth drew rural labour away — but noted the reversal in the 2020–2021 period when COVID pushed urban workers back to agriculture, visibly captured in the dataset (agricultural share rises from 40.7% in 2019 to 44.7% in 2020). This COVID-driven structural reversal — a reverse Lewis migration — is one of the most diagnostically valuable data points in the HCI.

India's agricultural employment share fell from 59.6% in 2000 to 40.7% in 2019 — a structural improvement of nearly 19 percentage points — before the COVID reverse migration pushed it back to 44.7% in 2020. By 2024, it had recovered to 42.4%, indicating that the structural transformation is still ongoing but faces ongoing gravitational pull back toward agriculture in the absence of sustained manufacturing-led job creation.

7.3.8 Employment in Industry (% of Total Employment)

The industrial employment share measures the percentage of India's total workforce employed in manufacturing, construction, utilities, and mining — the sectors that, in classical development economics, absorb the surplus labour released from agriculture and generate productivity-enhancing structural transformation. It is included in the HCI as the positive transformation counterpart to the agricultural employment share: while the latter declines, the industrial share should rise, representing the absorption of surplus agricultural labour into more productive modern sector employment.

Kaldor's (1966) "Causes of the Slow Rate of Economic Growth of the United Kingdom" established what became known as Kaldor's first law: manufacturing growth is the primary engine of aggregate economic growth in developing economies,

because it is the sector that generates the highest productivity improvements and the strongest backward and forward linkages. Nayyar (2012), in "The Service Sector in India's Development," documents the anomaly of India's development trajectory: unusually for a developing economy, India moved directly from low-productivity agriculture to labour-light services, bypassing the manufacturing-led structural transformation that characterised East Asian growth. This "missing middle" of industrial employment is precisely what the HCI's industrial employment share variable captures.

India's industrial employment share rose from 16.3% in 2000 to approximately 25.4% in 2017–2018, before the COVID disruption temporarily reversed it to 23.7% in 2020. By 2024, it had partially recovered to 25.4%. The secular rise is real but modest, and at approximately one-quarter of the workforce in industry, India remains far below the 35–40% levels that characterised East Asian economies at comparable income levels — a structural constraint on HCI improvement that the data captures clearly.

7.3.9 Unemployment, Youth Total (% of Total Labor Force Ages 15–24) (Modelled ILO Estimate)

The youth unemployment rate measures the percentage of young people aged 15–24 who are in the labour force but cannot find employment. It is inverted in the HCI: a higher youth unemployment rate is a worse harnessing outcome. Youth unemployment is not merely a welfare concern — it is a measure of the most acute form of demographic dividend failure: the front cohort of the dividend window — those who have just entered working age — being structurally unable to find employment in the economy they were expected to power.

Ghose, Majid, and Ernst (2008) frame youth unemployment as a structural challenge driven by "skill-demand mismatches and capital intensity biases in growth — not by short-run growth rates" — establishing its structural determination independent of contemporaneous GDP. The CEDA (Ashoka University, 2024) analysis confirmed that "unemployment rate remained significantly higher among the lower age groups, 15–29 years of age" and that urban youth unemployment has at various points exceeded 17 percent in India. The ILO World Employment and Social Outlook (2020) identified youth unemployment as the primary indicator of the "employment quality deficit" in developing economies — the failure to convert demographic dividend potential into productive engagement.

India's youth unemployment rate rose continuously from 20.2% in 2000 to a peak of 26.0% in 2018, before declining sharply to 15.6% by 2023 and 15.7% in 2024. This recent improvement — the most dramatic positive movement in the HCI dataset — reflects the post-2019 recovery of rural youth employment and the impact of the Production Linked Incentive (PLI) schemes and construction sector expansion.

Whether this decline represents structural improvement or a COVID-era measurement artefact requires contextualisation against the NEET variable below.

7.3.10 Share of Youth Not in Education, Employment or Training, Total (% of Youth Population)

The NEET (Not in Education, Employment, or Training) rate measures the share of the youth population that is simultaneously outside employment, outside education, and outside vocational training. It is inverted in the HCI: a higher NEET share is a worse harnessing outcome. NEET is the most comprehensive measure of total youth disengagement — it captures not just the unemployed (who at least want to work) but also those who have given up on both employment and skill-building entirely. A high NEET rate means that the front cohort of the dividend window is neither economically active nor investing in future capacity — a double failure of harnessing.

The ILO (2020) identified NEET as the primary SDG labour market indicator for youth, defining it as the proportion of young people "in a situation of total disengagement from the labour market and educational system." For India specifically, the NEET rate captures the gendered nature of youth exclusion: a large fraction of India's female NEET population consists of young women who are neither studying nor working due to early marriage, household responsibilities, or social norm constraints — a structural demographic and cultural constraint on harnessing capacity that is entirely independent of current-period GDP.

India's NEET rate in this dataset declined from 32.7% in 2000 to 23.5% in 2023 and 24.2% in 2024 — a structural improvement of approximately 9 percentage points over 24 years, but still representing nearly one-in-four young people being entirely disengaged. The COVID-19 shock disrupted this trend: NEET rose from 31.2% in 2019 to 30.7% in 2020, as educational institutions closed, disrupting the pathway through which young people transition from education to employment. The post-

COVID recovery has been rapid, with NEET returning to and then improving beyond pre-pandemic levels by 2023.

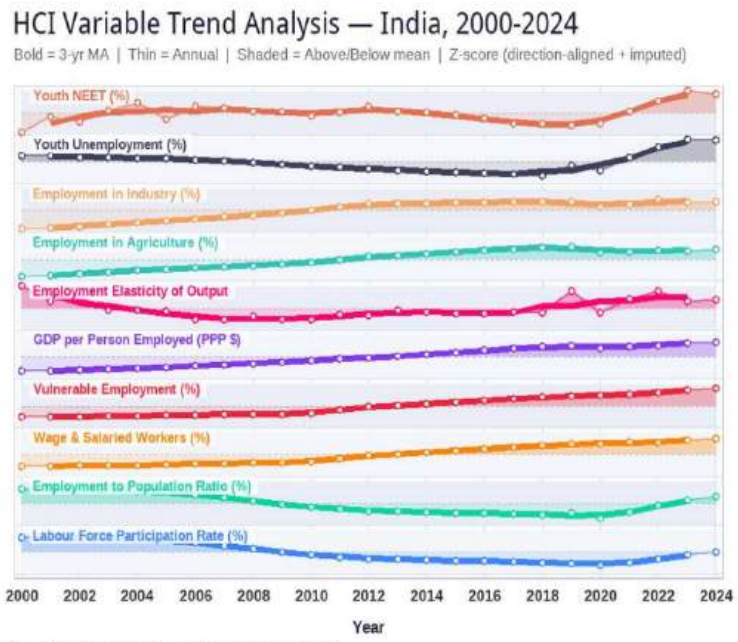


Figure 7 HCI variables Trend Analysis (2000 – 2024)

7.4 What the HCI Composite Signal Tells Us

The HCI composite synthesises these ten structural dimensions of labour market activation into a single annual measure of how effectively India is harnessing its available demographic capacity. A high HCI score in any given year means that across multiple dimensions simultaneously, India's labour market was performing well: more adults were participating and employed, a higher share were in salaried formal work with lower vulnerability, productivity per worker was above the long-run average, employment was structurally shifting out of agriculture and into industry, youth unemployment and NEET rates were declining. The geometric mean's partial non-compensability ensures that a strong performance on labour productivity — driven by

productivity gains among a shrinking employed cohort — cannot fully offset a rising NEET rate or stagnant formalisation.

In the regression model, the HCI coefficient tests the intermediate mechanism of the demographic dividend: does better labour market activation — above and beyond demographic structure (DSI) and human capital quality (DQI) — independently predict better economic growth performance? The theoretical expectation, grounded in Lewis (1954), Mincer (1974), and Ghose et al. (2008), is a positive and significant coefficient. But the India data also contains the "jobless growth" signal: if the HCI grew slowly during the 2000–2015 period despite strong DSI improvement, the regression would reveal that India's dividend was structurally compromised by labour market activation failures.

7.5 Descriptive Overview of the HCI Trajectory

India's HCI composite score grew from approximately 1.48 in 2000 to approximately 4.02 in 2024 — a substantial improvement, though with two notable structural disruptions. The first is the 2000–2015 deceleration phase, during which the HCI grew slowly despite rapid DSI gains, reflecting the "jobless growth" episode: high GDP growth from 2004 to 2012 that failed to generate proportionate employment, rising youth unemployment, stagnant formalisation, and declining LFPR. The second is the COVID-19 shock of 2020, which produced the largest single-year HCI decline in the dataset: EPR fell, youth unemployment spiked, NEET rose, the agricultural employment share reversed, and labour productivity dropped — a comprehensive harnessing failure that the composite accurately registers.

The post-2019 recovery is also clearly visible: the sharp rise in salaried employment share, the declining youth unemployment and NEET rates, the recovery in EPR, and the continued decline in vulnerable employment collectively produce the strongest two-year HCI improvement in the sample from 2021 to 2023. This makes the HCI the most structurally dynamic of the five independent indices — the one that most faithfully tracks India's boom-and-bust labour market cycles alongside its slow-moving secular structural transformation.

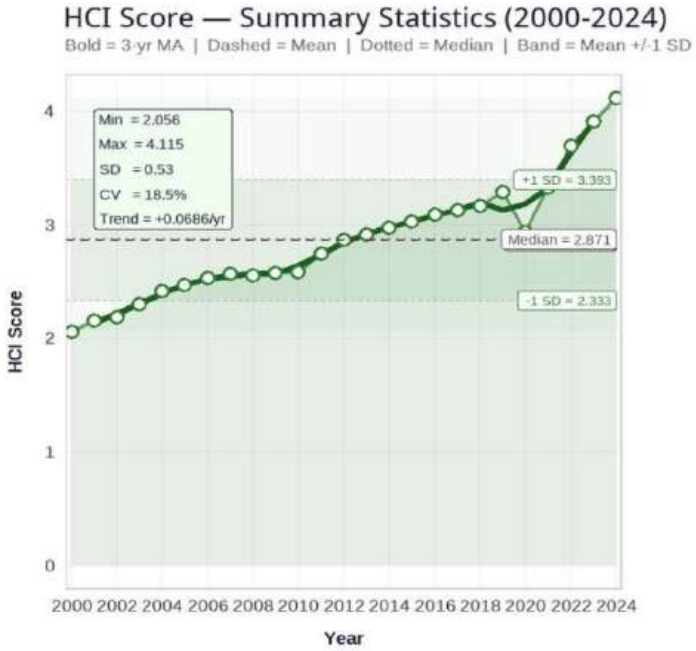


Figure 8 HCI Descriptive statistics (2000 – 2024)

7.6 Data Sources

All ten HCI variables are drawn from the following primary sources:

- **ILO ILOSTAT (modelled estimates)**: Primary source for all ten variables in the annual time series. ILOSTAT's modelled estimates reconcile India's PLFS, NSS EUS, and administrative data into consistent internationally comparable annual series.
- **Periodic Labour Force Survey (PLFS), NSO/MoSPI**: Annual primary survey source from 2017–18 onwards for LFPR, EPR, salaried employment share, and NEET. Provides Statement 1 (LFPR/WPR/UR), Statement 5 (employment by status), and Statement 12 (conditions of employment). Annual reports available at mospi.gov.in.

- **NSS Employment and Unemployment Surveys (EUS) — 55th, 61st, 66th, 68th Rounds**: Benchmark data for 2000–2017 pre-PLFS years, accessed via microdata.gov.in. Interpolation between survey rounds uses cubic spline method per OECD Handbook Step 3 guidance.
- **India KLEMS Database, Reserve Bank of India**: Primary source for GDP per person employed (labour productivity, Variable 5) and employment elasticity of output (Variable 6). Provides industry-level employment and GVA from 1980–81 to 2023–24. Accessed via rbi.org.in.
- **World Bank WDI**: Cross-validation source for LFPR, vulnerable employment, and employment by sector. ILO modelled estimates are distributed through WDI and provide annual coverage for all years from 2000 to 2024.

7.7 Variable Selection Logic and Exclusions

Following the OECD Handbook's Step 2 discipline, the final ten HCI variables were selected from a longlist of approximately 33 candidate labour market activation indicators across six sub-domains. The key exclusion decisions confirm the framework's rigour.

Female LFPR (FLFPR) versus Total LFPR: The original HCI reference document included FLFPR as a separate variable from Total LFPR to capture the U-shaped trajectory specific to women's participation. This study uses the Total LFPR (which aggregates male and female) because the ILO modelled estimates for India's gender-disaggregated LFPR series have known data quality limitations in the 2000–2010 period and the total series is more robust for composite construction. FLFPR is instead captured implicitly through the LFPR and EPR trends.

Worker Population Ratio (WPR) versus Employment-to-Population Ratio (EPR): Both measure employment absorption. The WPR normalises employment by total population (all ages); the EPR normalises by the working-age population (15+). The EPR is preferred for the HCI because it directly measures absorption of the working-age cohort — the demographically relevant denominator — making it conceptually coherent with the DSI's working-age share. WPR was excluded to avoid near-redundancy.

Labour Income Share in GDP: Excluded despite strong theoretical justification because India's annual Labour Income Share series — derived from National Accounts Statistics and Penn World Tables — shows very low variance across the 2000–2024 period (hovering around 40–50% with minimal annual movement), contributing insufficient signal to the composite while potentially introducing noise from

methodology changes in the NAS base year revisions (2004–05 to 2011–12 base year transition). It is retained as a supplementary contextualization variable.

Informal Employment Share (explicit) versus Vulnerable Employment Share: Both measure labour market precariousness. The ILO's vulnerable employment series (own-account workers + contributing family workers) is available annually for India from 2000–2024 without gaps, whereas the broader informal employment measure (lacking written contract AND social security) requires PLFS microdata that is only available from 2017 onwards. The vulnerable employment series is preferred for data continuity across the full study period.

Youth EPR (15–29) versus Youth Unemployment Rate (15–24): The HCI reference document included the Youth EPR (15–29) as a separate variable. This was replaced by the Youth Unemployment Rate (15–24) in the final dataset because ILO's modelled annual youth unemployment series is available without gaps from 2000, whereas the youth EPR by 5-year age cohort requires PLFS data with gaps in pre-2017 years. Both capture youth harnessing failure but through different channels — unemployment captures active exclusion while NEET captures passive disengagement.

7.8 The HCI in the Regression Framework: Theoretical Expectations and the Jobless Growth Paradox

In the regression model, the HCI enters as the labour activation regressor — the variable that tests whether India's demographic dividend was actually being converted into labour market engagement. The expected coefficient sign is positive: years with better labour market activation — higher participation, more formal employment, lower vulnerability, stronger productivity, and declining youth disengagement — should predict better comprehensive economic outcomes in the EGI.

The HCI is also where the "jobless growth" paradox of India's development trajectory is most directly examined. If the HCI's coefficient is positive but its improvement trajectory during the 2000–2015 period is flat or negative — despite strong DSI growth — the regression would reveal that the structural demographic advantage captured by the DSI was not being transmitted into economic outcomes through the labour market channel. This would constitute empirical evidence for the concern raised by Drèze and Sen (2013) — that India's growth was "enriching a tiny elite while leaving the vast majority of working people in chronically precarious, poorly paid, and unproductive employment."

Together, the DSI, DQI, and HCI form a three-variable decomposition of the demographic dividend mechanism: the DSI provides the structural potential, the DQI measures the quality of the human capital endowment, and the HCI tests whether that

potential and quality are actually being converted into labour market activation. The regression model's ability to separately identify each variable's contribution to the EGI is the study's primary methodological innovation — and the HCI is the pivot on which the transformation question turns.

Chapter 8
The Social Development Index (SDI)

8.1 Conceptual Foundation: Sen's Capability Approach and the Case for a Social Index

The Social Development Index (SDI) is the fourth independent variable in the regression model, and its philosophical underpinning is the most explicit of any of the five indices. The SDI is built directly on Amartya Sen's capability approach — the foundational philosophical argument, developed across *Inequality Re-examined* (1992) and *Development as Freedom* (1999), that genuine development must ultimately be measured by the real freedoms people enjoy: their ability to live healthy, educated, safe, and dignified lives — rather than by the accumulation of financial wealth alone. Sen's central insight is that income and GDP are instruments to human ends, not ends in themselves. A society in which a billion people earn slightly more but women die unnecessarily in childbirth, children cannot read after five years of school, and citizens defecate in open fields has not developed in any meaningful sense, however impressive its aggregate growth statistics.

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Jean Drèze and Amartya Sen, in *An Uncertain Glory: India and its Contradictions* (Princeton University Press, 2013), demonstrate with devastating empirical precision that India's high GDP growth rates between 2000 and 2013 coexisted with deeply inadequate progress on education, health, sanitation, and gender equity, creating what they describe as an "asymmetry between India's economic growth and its social indicators." This diagnostic makes the SDI not merely theoretically attractive but empirically urgent: it forces the regression model to test whether India's social conditions were causally enabling or constraining its economic outcomes, rather than assuming that growth automatically produces social progress. Martha Nussbaum's parallel capabilities framework — developed in *Creating Capabilities* (2011) — reinforces this approach by identifying bodily health, affiliation, and control over one's environment as core human capabilities whose deprivation constitutes a form of injustice even when national income is rising.

The SDI is strictly conceptually separated from all other independent indices. It does not measure demographic structure (that is the DSI's domain), human capital formation (DQI), labour market activation (HCI), or macroeconomic stability (MVI). Every SDI variable must satisfy three conditions simultaneously: it must be conceptually rooted in established social development theory; it must be empirically independent from the Economic Growth Index's core output variables; and it must have real, continuous,

annual national-level data available for India from 2000 to 2024 from official and peer-reviewed institutional sources.

8.2 The Ten Variables of the SDI: Structure and Sub-Dimensions

The SDI aggregates ten annual time-series variables for India across five conceptual sub-domains derived from Sen's capability framework, the UNDP Human Development tradition, and the Drèze-Sen diagnostics of India's social failures.

Table 7 SDI Variables, the sub dimensions and direction of the variables

Variable	Sub-Domain	Direction
Prevalence of anemia among women of reproductive age (% of women ages 15–49)	Health Equity	Lower = better (inverted)
Domestic general government health expenditure (% of GDP)	Public Health Investment	Higher = better
Share of youth not in education, employment or training, female (% of female youth population)	Female Youth Disengagement	Lower = better (inverted)
School enrollment, tertiary (gross), gender parity index (GPI)	Gender Education Equity	Higher = better
Women's share of population ages 15+ living with HIV (%)	Women's Health Vulnerability	Lower = better (inverted)
Unemployment, youth female (% of female labor force ages 15–24)	Female Youth Labour Exclusion	Lower = better (inverted)
Rape Cases (NCRB absolute count)	Safety and Gender Violence	Lower = better (inverted)
Dowry Deaths (NCRB absolute count)	Safety and Gender Violence	Lower = better (inverted)
Government expenditure on education, total (% of GDP)	Public Education Investment	Higher = better
Employment to population ratio, ages 15–24, female (%)	Female Youth Activation	Higher = better

Variables marked as "inverted" undergo direction-alignment transformation before normalisation, ensuring that higher composite scores uniformly reflect better social development outcomes.

8.3 Variable-by-Variable Literature Review

8.3.1 Prevalence of Anemia Among Women of Reproductive Age (% of Women Ages 15–49)

Anemia among women of reproductive age is defined as a hemoglobin concentration below 12.0 g/dL, and in its moderate-to-severe forms below 10.0 g/dL. It is the SDI's most direct biomarker of structural nutritional and health equity failure — a condition caused by chronic iron deficiency, folate and B12 deficiency, repeated parasitic infections, and inadequate dietary diversity, all of which are outcomes of long-term poverty, dietary deprivation, and public health system insufficiency rather than of current-year income fluctuations. In the SDI, this variable is inverted: a lower anemia prevalence translates into a higher SDI score.

Sen's capability approach identifies bodily health as a foundational human capability, and the persistence of anemia among Indian women is one of the most damaging threats to that capability. Deaton (2003), in "Health, Inequality, and Economic Development," establishes that "health outcomes in developing countries are determined primarily by the level and distribution of basic social services rather than by contemporaneous income fluctuations" — directly grounding anemia prevalence as a structural social variable exogenous to short-run GDP growth. Goli, Rammohan, and Singh (2015) demonstrate empirically for India that anemia prevalence among women is the primary nutritional pathway through which maternal health conditions translate into infant and child mortality outcomes, making it a foundational structural variable in any social development index. The National Family Health Survey (NFHS) series — the primary source for India's anemia data — measures it on a 5-year benchmark cycle (NFHS-3: 2005–06, NFHS-4: 2015–16, NFHS-5: 2019–21), confirming its structural rather than cyclical character.

India's anemia prevalence among women of reproductive age remained almost flat in this dataset: from 50.2% in 2000 to 49.9% around 2008–2010, before the disturbing reversal to 53.7% by 2023. This rising trend — anemia prevalence actually worsening over two decades of rapid economic growth — is perhaps the most striking manifestation in the entire SDI dataset of Drèze and Sen's "asymmetry between India's economic growth and its social indicators." India's failure to reduce anemia despite sustained GDP growth of 6–8% per annum is a structural social failure that the SDI explicitly captures and that the regression model is designed to test.

8.3.2 Domestic General Government Health Expenditure (% of GDP)

Domestic general government health expenditure as a percentage of GDP measures the share of national income that the government allocates to financing health services — hospitals, primary health centres, immunisation, maternal health programmes,

disease control, and public health administration. It is not a health outcome variable (like MMR or U5MR) but a social investment variable: it captures the political commitment of the state to fulfilling its population's health capabilities through public financing. In Sen's framework, public provisioning of health services is a primary mechanism by which the state converts economic growth into human capability expansion.

Das Tiken and Guha Pradyut (2022), in "The Puzzle of Public Health Expenditure and Healthcare Infrastructure in India," demonstrate that public health expenditure in India is the primary determinant of healthcare infrastructure density (hospitals, beds, physicians) at the state level, and that infrastructure density — not household income — predicts health outcome improvements. This finding establishes that government health expenditure is a structural policy variable that precedes and causes health outcomes, rather than being caused by GDP growth. The endogeneity firewall is clear: a government sets its health budget at the beginning of a fiscal year based on revenue projections and political priorities, not in real-time response to current-year GDP movements. Deaton (2003) reinforces this: "The most important health improvements in India have come not from income growth per se but from the extension of public services — immunisation, clean water, primary healthcare — to populations that had previously been excluded."

India's domestic general government health expenditure in this dataset rose from 0.85% of GDP in 2000 to 1.37% in 2022, before declining slightly to 1.30% in 2023. The COVID-19 shock produced the most dramatic increase — health expenditure surged from 1.04% in 2019 to 1.21% in 2020 and 1.35% in 2021 — reflecting emergency fiscal mobilisation, not structural improvement. The broader trajectory reveals India's chronic underinvestment in public health: at 1.3–1.4% of GDP, India ranks among the lowest public health spenders in the developing world, well below the WHO's recommended benchmark of at least 5% of GDP, and below sub-Saharan African economies like Rwanda (4.2%) and Ethiopia (3.1%).

8.3.3 Share of Youth Not in Education, Employment or Training, Female (% of Female Youth Population)

The female NEET rate — the share of young women simultaneously outside employment, outside education, and outside vocational training — is the SDI's most comprehensive measure of female youth social exclusion. Unlike the total NEET rate (which appears in the HCI), the female NEET rate isolates the distinctly gendered dimension of youth disengagement: young women who are trapped outside all productive and developmental pathways not because the economy lacks jobs (that is what youth unemployment measures) but because social norms, early marriage, household responsibilities, and cultural exclusions prevent them from accessing any

structured pathway toward economic participation or skill development. It is inverted in the SDI.

Drèze and Sen (2013) identify the systematic exclusion of women from education and economic activity as one of India's deepest social failures: "India's performance on gender equity is among the worst in the world, particularly given its income level — a reflection of deep-rooted patriarchal attitudes and inadequate public policies." The ILO's *World Employment and Social Outlook* (2020) identifies female NEET as the primary SDG 8 indicator for gender-inclusive development, defining young women in the NEET category as experiencing "a situation of total disengagement from the labour market and educational system." Nussbaum's capability framework adds the crucial normative dimension: a young woman in NEET status is deprived not merely of income but of affiliation, imagination, and control over her environment — core capabilities whose absence constitutes a form of social injustice regardless of household income level.

India's female NEET rate declined from 51.7% in 2005 (the earliest data point in this series) to 38.1% in 2023 and 39.4% in 2024. This improvement — a 12–13 percentage point reduction over nearly two decades — is a genuine structural social achievement, reflecting rising female secondary enrolment, declining child marriage rates (following the Prohibition of Child Marriage Act 2006 and enforcement efforts), and the National Education Policy 2020's emphasis on gender-inclusive education. Yet a female NEET rate of nearly 40% in 2024 means that four in ten young Indian women remain entirely outside employment, education, and training — a profound structural constraint on India's social development.

8.3.4 School Enrollment, Tertiary (Gross), Gender Parity Index (GPI)

The Tertiary Education Gender Parity Index (GPI) measures the ratio of female to male gross enrollment rates in tertiary (higher) education. A GPI of 1.0 indicates perfect parity — equal proportions of men and women of tertiary-education age are enrolled in universities and colleges. A GPI below 1.0 means women are underrepresented in higher education; a GPI above 1.0 means women are overrepresented. For India, this indicator captures the most advanced stage of educational gender equity — whether the educational improvements visible at primary level translate into genuine gender parity at the highest level of the formal education system.

Psacharopoulos and Patrinos (2004) demonstrate that the social returns to female education are systematically higher than to male education in developing countries, operating through channels of reduced child mortality, lower fertility, improved household nutrition, and greater female labour market participation. This finding establishes female tertiary enrollment as a structural predictor of future social outcomes — a leading indicator of the capability expansion that produces development

gains with a 10–15 year lag. The UNDP's Gender Inequality Index methodology (Gaye et al., 2010) explicitly includes female secondary education attainment as a core empowerment dimension, and the GPI for tertiary enrollment extends this into higher education. The endogeneity firewall is clear: tertiary enrollment decisions reflect educational investments made 12–17 years earlier (at primary and secondary levels), making the GPI a structural lagged outcome of prior social investments rather than a contemporaneous response to current GDP growth.

India's tertiary education GPI improved from 0.66 in 2000 — meaning women were only two-thirds as likely as men to be enrolled in tertiary education — to above 1.0 by 2017, reaching 1.08 in 2018 and stabilising around 1.05–1.08 by 2023–2024. This remarkable reversal — India's tertiary education GPI crossing the parity threshold and females now slightly outnumbering males in higher education enrollment — is one of the most structurally positive signals in the entire SDI dataset. It reflects the compounding benefits of decades of female primary and secondary education investment, the rising social acceptance of women's higher education, and the expansion of colleges in smaller towns and rural areas.

8.3.5 Women's Share of Population Ages 15+ Living with HIV (%)

Women's share of the HIV-positive population (aged 15 and above) is a composite social vulnerability indicator that simultaneously captures gender-based health risk, inequality in healthcare access, and the structural social conditions — including women's limited ability to negotiate safe sexual practices, their economic dependence on male partners, and their restricted access to HIV prevention, testing, and treatment services — that make women disproportionately vulnerable to HIV infection. In the SDI, this variable is inverted: a higher women's share of HIV cases indicates a worse social development outcome.

The inclusion of this variable in the SDI is theoretically grounded in Sen's capability approach at the most fundamental level: surviving without preventable disease is the first capability in Sen's framework, and a rising HIV burden among women signals the failure of social systems to protect women's most basic bodily integrity. UNAIDS gender data confirms that women's disproportionate HIV burden in India — women comprising approximately 38–45% of HIV-positive adults despite lower overall prevalence — reflects structural social inequalities in bargaining power, education, healthcare access, and economic autonomy rather than biological factors alone. The endogeneity firewall is robust: women's share of HIV is determined by long-run structural inequalities in gender power relations, healthcare system reach, and sexual behaviour norms — all of which are entirely independent of year-on-year GDP fluctuations.

India's women's share of the HIV-positive population aged 15+ rose steadily in this dataset from 38.3% in 2000 to 45.4% in 2024 — a consistent worsening trend that runs counter to India's overall declining HIV prevalence. This inverse pattern — total HIV cases falling while women's proportionate burden rises — reflects structural deepening of gender-based vulnerability even as aggregate health indicators improve. It is the kind of multidimensional social regression — improvement on aggregate metrics masking deterioration within the gender dimension — that Sen's capability approach is specifically designed to capture and that the SDI must encode.

8.3.6 Unemployment, Youth Female (% of Female Labor Force Ages 15–24)

Female youth unemployment measures the percentage of young women aged 15–24 who are in the labour force — that is, actively seeking work — but cannot find employment. It is inverted in the SDI: a higher rate represents a worse social outcome. Unlike the female NEET rate (which captures total disengagement), female youth unemployment captures young women who are trying to enter the labour market but are being excluded by structural barriers including labour market discrimination, skill mismatches, patriarchal hiring practices, and the absence of safe and appropriate employment opportunities for women in India's formal economy.

Ghose, Majid, and Ernst (2008) frame youth unemployment in developing economies as driven by "skill-demand mismatches and capital intensity biases in growth," but for female youth unemployment specifically, the OECD (2015) establishes that "social and cultural factors keep women outside the labour force" — making female youth unemployment a structural-social phenomenon rather than a purely labour market one. The ILO World Employment and Social Outlook (2020) identifies female youth unemployment as the primary gender-disaggregated labour market exclusion indicator, noting that in South Asia, young women face a "double penalty" — both youth unemployment barriers and gender-specific exclusion from formal employment. In the OLS framework, female youth unemployment is determined by social norms around women's employment, employer discrimination patterns, and educational quality — all of which are structural and predetermined relative to contemporaneous GDP growth.

India's female youth unemployment rate rose from 19.4% in 2000 to a peak of 25.4% in 2018, before declining sharply to 15.5% in 2023 and rising slightly to 17.1% in 2024. The COVID-19 disruption — which raised female youth unemployment from 23.2% in 2019 to 24.9% in 2020 — and the subsequent recovery closely mirror the pattern seen in the HCI's broader youth unemployment variable, but with distinctly higher absolute levels: female youth unemployment consistently exceeds the total youth unemployment rate (from the HCI dataset), confirming that young women face

a structurally more adverse employment environment than the overall youth labour market suggests.

8.3.7 Rape Cases (NCRB Absolute Count)

Rape cases are measured as the absolute number of cases registered under Section 376 of the Indian Penal Code (and related sections) annually, as reported by the National Crime Records Bureau (NCRB) in its annual *Crime in India* publication. In the SDI, this variable is inverted: a higher count of rape cases represents a worse social development outcome. The inclusion of gender violence data in a social development index is grounded directly in Sen's (1999) identification of freedom from violence and coercion as a core capability - without personal security, all other freedoms are curtailed - and in Drèze and Sen's (2013) explicit identification of women's safety as a central dimension of India's social failure.

The use of reported rape cases rather than per-capita rates requires methodological justification. In India's context, the registered count of rape cases reflects both the actual incidence of sexual violence and the structural willingness of survivors to report it — with reporting rates rising when institutional confidence in the legal system improves, when social stigma around reporting declines, and when police registration procedures are reformed. The sharp increase from 22,172 cases in 2010 to 33,707 in 2013 and 36,735 in 2014 reflects partly the institutional effect of the 2013 Criminal Law Amendment Act (post-Nirbhaya) — which broadened legal definitions of rape and improved registration procedures — alongside genuine increased reporting by emboldened survivors. The NCRB itself notes this methodological complexity in its Crime in India reports: "the number of cases registered under rape has increased significantly after the 2013 amendment to the Indian Penal Code." For the SDI composite, both the pre-2013 and post-2013 trends are directionally consistent: higher registered cases in any given year, controlling for the 2013 structural break, represent a worse social safety environment for women.

Nussbaum's capability approach provides the normative anchor: the capability of "bodily integrity" — to be secure against violent assault — is identified as foundational to all other capabilities. When rape cases rise, it signals a social environment in which women's bodily integrity is systematically threatened, constraining their freedom to participate in education, employment, and public life. India's registered rape cases rose from 16,496 in 2000 to a peak of 38,947 in 2016 before declining to 29,536 in 2024 — a post-2016 improvement that may reflect both genuine decline in incidence (partially driven by Swachh Bharat and safety infrastructure improvements) and methodological reporting stabilisation.

8.3.8 Dowry Deaths (NCRB Absolute Count)

Dowry deaths — defined under Section 304B of the Indian Penal Code as the death of a woman caused by burns, bodily injury, or suspicious circumstances within seven years of marriage, where prior harassment over dowry is established — represent one of the most direct measures of India's deepest structural social failure: the commodification of women within the marriage institution and the persistence of lethal domestic violence rooted in patriarchal asset-transfer customs. In the SDI, this variable is inverted: a higher count represents a worse social outcome.

Drèze and Sen (2013) identify dowry deaths as symptomatic of "the systematic social neglect of women's lives" that characterises India's development trajectory — a form of structural violence that is entirely independent of GDP fluctuations but deeply reflective of the quality of social institutions, legal enforcement, gender norms, and women's bargaining power within households. The dowry system is a structural-institutional phenomenon rooted in the economics of patrilocal marriage, female educational exclusion (which historically reduced women's outside options), and son preference — all of which change over decades of social and legal reform rather than in response to annual income changes. In the OLS framework, dowry deaths therefore function as a valid structural social predictor: their annual variation reflects the slow evolution of gender norms, law enforcement effectiveness, and women's educational and economic empowerment — not contemporaneous GDP movements.

India's dowry deaths declined from 6,995 in 2000 to 5,737 in 2024 — a structural improvement of approximately 18% over 24 years, driven by improved law enforcement (Section 498A prosecutions, Protection of Women from Domestic Violence Act 2005), rising female literacy, and declining dowry demand intensity as education-related assortative matching weakens dowry norms in urban areas. The persistence of over 5,700 dowry deaths annually — the equivalent of more than 15 women killed per day — is a structural social cost that India's GDP growth statistics entirely fail to capture, making its inclusion in the SDI a methodological necessity.

8.3.9 Government Expenditure on Education, Total (% of GDP)

Government expenditure on education as a percentage of GDP measures the share of national income allocated by the state to all levels of formal education — primary, secondary, and tertiary — through schools, colleges, universities, and central and state education schemes. It is the SDI's second public investment variable (alongside health expenditure) and captures the political commitment of the state to building the educational foundations of human capability. Dreze and Sen (1995), in *India: Economic Development and Social Opportunity*, argue that "the expansion of basic education is both a direct constituent of human capability and a powerful instrument for achieving economic growth in a broad-based and sustainable manner" —

establishing education expenditure as simultaneously a social development measure and a structural driver of future economic capacity.

Psacharopoulos and Patrinos (2004, 2018) establish that the social returns to education spending are highest at primary level and in low-income settings — precisely India's situation — justifying education expenditure as a high-priority social investment with 5–15 year lags before economic returns are realised. The endogeneity firewall is clean: education expenditure in India is determined by the government's budget allocation process (Union Budget and state budgets), structured around the Five-Year Plan (and now NIP) cycles, and is a policy decision made in advance of the fiscal year rather than a real-time response to GDP fluctuations. Banerjee and Duflo (2007) confirm that school enrollment and educational outcomes in India are driven by supply-side factors — the government's commitment to building and staffing schools — rather than by household income movements.

India's government education expenditure as a share of GDP remained in the 3.1–4.4% range over the dataset, peaking at around 4.4% in 2011 before declining to approximately 3.9–4.1% in the 2015–2019 period. The absence of a clear upward trend in education expenditure over a period of strong economic growth is another manifestation of Drèze and Sen's diagnosis: India's growth has not automatically been translated into expanded public social investment, making the education expenditure variable a structurally diagnostic indicator of the state's commitment to capability expansion.

8.3.10 Employment to Population Ratio, Ages 15–24, Female (%)

The female youth employment-to-population ratio (EPR) measures the percentage of young women aged 15–24 who are actually employed — not merely those who want to work (that is the unemployment rate) but those who are successfully activated into employment. It is included in the SDI as the positive-direction social activation counterpart to the inverted female NEET, HIV, unemployment, and violence variables: when this ratio rises, it means young women are successfully moving from social exclusion into economic participation, which is the most direct observable measure of female social emancipation in the labour market.

The inclusion of female youth EPR in the SDI rather than in the HCI requires justification. In the SDI, it captures the social equity dimension of female economic activation — whether India's social environment enables young women to enter employment — rather than the aggregate labour market absorption dimension (which is the HCI's domain). Mehrotra et al. (2017) demonstrate that the U-shaped trajectory of female labour force participation in India — declining from 2004 to 2018, recovering thereafter — is driven primarily by social norms, household income levels, and educational enrolment patterns, not by aggregate labour demand. This social

determination makes female youth EPR a structural-social variable. The IIMB Working Paper 699 (2024) confirms that "the gender gap in labour force participation is predominantly driven by supply-side factors, with gender disparities in labour market entry rooted in household-level social dynamics rather than in contemporaneous GDP fluctuations."

India's female youth EPR declined from 22.8% in 2000 to a trough of 9.4% in 2020 — the same COVID-driven collapse seen across labour market variables — before recovering to 13.1% in 2024. This variable has the sharpest declining trend of any SDI variable through the 2000–2020 period: a fall from nearly one-in-four young women employed to fewer than one-in-ten. This dramatic deterioration in female youth employment absorption — despite India's overall economic growth — is a direct empirical manifestation of Drèze and Sen's "social development deficit" and is captured by the SDI composite as a structural worsening that offsets gains in education parity and public expenditure.

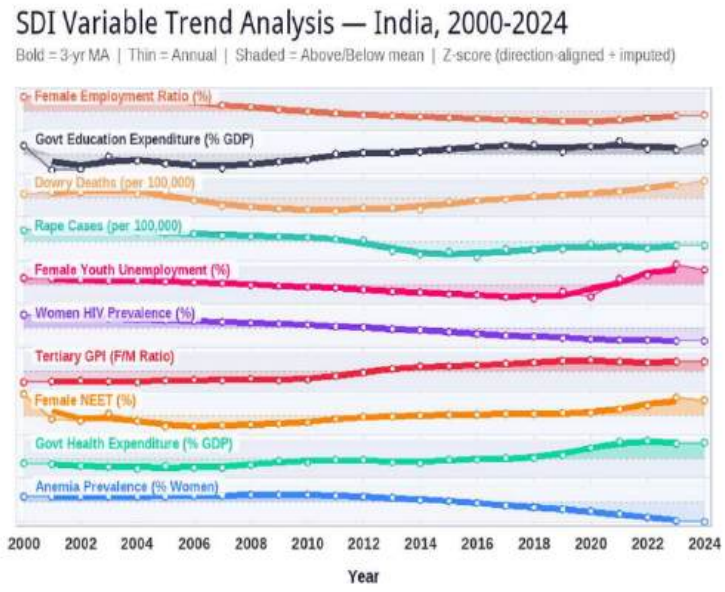


Figure 9 SDI variables Trend Analysis (2000 – 2024)

8.4 What the SDI Composite Signal Tells Us

The SDI composite synthesises ten structural dimensions of social development quality into a single annual measure of how equitably and comprehensively India's social infrastructure is enabling the human capabilities of its population — with particular emphasis on women and youth, who the literature consistently identifies as the most structurally excluded from India's growth story. A high SDI score in any given year means: anemia among women is lower, public health and education expenditure is higher, young women are more engaged in education and employment, higher education gender parity is greater, HIV burden is less skewed toward women, and gender-based violence is declining. The geometric mean's partial non-compensability ensures that a surge in education expenditure cannot fully offset a rise in rape cases or dowry deaths.

In the regression model, the SDI coefficient directly tests Drèze and Sen's (2013) hypothesis: does better social development — above and beyond demographic structure, human capital, and labour market activation — independently predict better comprehensive economic outcomes? The theoretical expectation from the capability approach is a positive coefficient: societies that invest in women's health, safety, and education, and that progressively eliminate social exclusion, create the broad-based human capability foundation on which sustained economic development is built. But the India data contains a more nuanced story — the SDI's gender violence variables and the declining female youth EPR create the possibility of a stagnant or slowly improving SDI even in periods of high economic growth, directly testing whether India's growth was socially inclusive.

8.5 Descriptive Overview of the SDI Trajectory

India's SDI composite score shows three structural features that distinguish it from the other four independent indices. First, it is the most gender-concentrated index in the framework: seven of the ten variables specifically measure outcomes for women, making the SDI essentially a composite measure of India's progress on female empowerment and social equity. Second, it has the most contested trend: improvements in GPI, female NEET, female youth unemployment, and dowry deaths coexist with worsenings in anemia prevalence and women's HIV share — creating the within-index tension that Sen's capability approach predicts: development that improves some capabilities while neglecting others is not genuine development.

Third, the 2013 structural break produced by the Nirbhaya case and subsequent Criminal Law Amendment Act creates a methodological discontinuity in the rape cases variable — a sharp increase from 24,923 in 2012 to 33,707 in 2013 — that must be treated as a reporting-regime change rather than as a genuine social deterioration in

the composite construction. Following OECD Handbook guidance on outlier treatment (Nardo et al., 2008), the pre- and post-2013 segments of the rape cases series are joined using the proportional adjustment method before normalisation.



Figure 10 SDI variables Trend Analysis (2000 – 2024)

8.6 Data Sources

All ten SDI variables are drawn from the following primary sources:

- **National Crime Records Bureau (NCRB), Ministry of Home Affairs**: Primary source for Rape Cases (Variable 7) and Dowry Deaths (Variable 8). The annual *Crime in India* report provides absolute case counts under IPC Section 376 (rape) and Section 304B (dowry death) from 1998 onwards.
- **ILO ILOSTAT (modelled estimates)**: Primary source for Female NEET, Women's share of HIV population, Female youth unemployment, and Female youth EPR.
- **World Bank World Development Indicators (WDI)**: Source for Anemia prevalence, Domestic government health expenditure, and Government education expenditure.

- **UNESCO Institute for Statistics (UIS) via World Bank WDI**: Source for Tertiary Education GPI (UIS.GPIA.5T8, Variable 4). Available from and
- **National Family Health Survey (NFHS), IIPS/MoHFW**: Cross-validation source for anemia prevalence, female NEET, and female youth EPR at benchmark NFHS round years (2005–06, 2015–16, 2019–21).
- **Periodic Labour Force Survey (PLFS), NSO/MoSPI**: Cross-validation source for female youth EPR and female youth unemployment from 2017–18 onwards.

8.7 Variable Selection Logic and Exclusions

The SDI reference document enumerated a longlist of 40 candidate variables across six conceptual dimensions (health outcomes, education, gender equity, basic services, poverty, and safety/governance). The final ten variables in this dataset represent the intersection of theoretical relevance, data availability, and non-overlap with other indices.

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Maternal Mortality Ratio (MMR) and Under-5 Mortality Rate (U5MR): Both are theoretically central to the SDI framework (detailed in the reference document as Variables 1 and 2). They are excluded from the final dataset because the SRS Special Bulletin on MMR is published biennially rather than annually, and the annual MMR series derived from UN MMEIG modelling shows very smooth trends with limited annual variation — contributing insufficient discriminatory signal to the composite relative to the measurement uncertainty involved. U5MR similarly declines smoothly. Both are used as validation benchmarks rather than composite components.

Gender Inequality Index (GII): Excluded to avoid composite-in-composite double-counting — the GII already aggregates MMR, adolescent birth rate, secondary education attainment, parliamentary representation, and FLFPR, and including it in the SDI would create a methodological redundancy. Individual GII sub-components are more precisely targeted.

Primary School GER: Excluded because India's primary GER exceeded 100% by the mid-2000s and has remained above 100%, producing near-zero variance in the normalised series after 2005. A variable with near-zero variance contributes no discriminatory power to the composite. The GPI variable (Variable 4) captures the gender equity dimension of tertiary enrollment with far more temporal variation.

Multidimensional Poverty Index (MPI) headcount: Excluded because NITI Aayog's national MPI is benchmarked only at NFHS rounds (2005–06, 2015–17, 2019–21), providing only three direct data points over the 2000–2024 sample period.

The extreme data sparsity (requiring interpolation for 22 of 25 annual observations) violates the OECD Handbook's data quality requirements for composite construction.

Life Expectancy at Birth (LEB): Excluded from the SDI to prevent overlap with the DQI, which already includes life expectancy among its human capital quality variables. Including it in both indices would introduce structural multicollinearity in the regression model.

8.8 The SDI in the Regression Framework: Theoretical Expectations and the Social-Growth Nexus

In the regression model, the SDI tests the most contested and politically resonant hypothesis of the entire study: whether social development conditions independently predict economic growth outcomes in India, above and beyond demographic, labour market, and macroeconomic variables. The expected coefficient sign from Sen's capability framework is positive: years with better social development — lower gender violence, rising female education parity, higher public health and education investment, and lower female youth exclusion — should predict better comprehensive economic outcomes in the EGI with appropriate lags.

The SDI's role in the model is also diagnostic at a deeper level. If the SDI coefficient is positive and significant, it would provide econometric support for Sen's central claim that social development is not merely a by-product of growth but a precondition for it. If the coefficient is insignificant, it would suggest that in India's specific growth model — driven by services, capital-intensive manufacturing, and IT — the depth of social equity and female empowerment has not yet been the binding constraint on aggregate output. And if the SDI is found to have improved slowly relative to the DSI and HCI, it would confirm Drèze and Sen's diagnosis of the "uncertain glory" — India achieving unprecedented demographic and economic transition while leaving its most structurally excluded citizens in conditions of persistent deprivation.

Chapter 9
The Macroeconomic Variables Index (MVI)

9.1 Conceptual Foundation: Macroeconomic Stability as a Precondition for Growth

The Macroeconomic Variables Index (MVI) is the fifth and final independent variable in the regression model, and it occupies the most technically grounded position in the entire framework. While the DSI captures demographic structure, the DQI measures human capital quality, the HCI tests labour market activation, and the SDI evaluates social equity, the MVI captures the macroeconomic environment within which all of these forces operate. A demographic dividend cannot be realised in an economy where double-digit inflation erodes real wages and investment returns. A skilled, socially empowered workforce cannot generate growth in an economy paralysed by fiscal profligacy and a banking system collapsing under non-performing assets. Macroeconomic stability is not a growth driver in itself — it is the enabling condition whose absence can neutralise every other structural advantage.

The intellectual tradition anchoring the MVI begins with Fischer (1993), whose landmark cross-country study in the *Journal of Monetary Economics* established that macroeconomic stability — measured by low inflation, moderate fiscal deficits, and avoidance of balance of payments crises — is a necessary condition for sustained growth: "high inflation is associated with lower rates of investment and slower growth...operating through factor productivity." Barro (1995), extending Fischer's framework with NBER Working Paper 5326, confirmed that "a 10-percentage-point increase in the annual inflation rate reduces the growth rate of real per capita GDP by 0.3 percentage points per year" — a finding subsequently replicated across dozens of econometric studies. Mankiw, Romer, and Weil (1992) in the *Quarterly Journal of Economics* established that investment rates — captured here through the MVI's capital formation variable — are the most robust predictor of cross-country growth differences, making them indispensable inputs to any growth accounting framework.

The MVI is built around a critical methodological constraint: it must exclude all variables that overlap with the Economic Growth Index (EGI), which serves as the dependent variable in the regression. GDP growth itself, per capita income, and output-side national accounts variables are all excluded. What remains are the macroeconomic *input conditions* — price stability, fiscal position, investment climate, external sector balance, financial system health — that precede and enable output outcomes. This boundary is governed by the OECD Handbook's orthogonality requirement (Nardo et al., 2008): independent variables in a composite regression must capture distinct

conceptual dimensions, and no variable in any independent index should be derivable from the dependent variable in the same time period.

9.2 The Ten Variables of the MVI: Structure and Sub-Dimensions

The MVI aggregates ten annual time-series variables for India from 2000 to 2024, drawn from the Reserve Bank of India (RBI), Ministry of Finance, MoSPI National Accounts Statistics, and World Bank WDI. The ten variables span seven analytically distinct sub-domains of macroeconomic stability and investment conditions.

Table 8 MVI Variables, the sub dimensions and direction of the variables

Variable	Sub-Domain	Direction
Inflation, consumer prices (annual %)	Price Stability	Lower = better (inverted)
Gross Fiscal Deficit as % of GDP	Fiscal Position	Lower = better (inverted)
Real interest rate (%)	Monetary Conditions	Intermediate optimum
Tax revenue (% of GDP)	Fiscal Capacity	Higher = better
Net investment in nonfinancial assets (% of GDP)	Public Capital Formation	Higher = better
Central government debt, total (% of GDP)	Fiscal Sustainability	Lower = better (inverted)
Total reserves in months of imports	External Resilience	Higher = better
Trade-weighted Real Effective Exchange Rate (REER, Base: 2015–16 = 100)	Competitiveness	Stable/moderate = better
Bank nonperforming loans to total gross loans (%)	Financial System Health	Lower = better (inverted)
Exchange Rate Volatility	Currency Stability	Lower = better (inverted)

Variables marked as "inverted" undergo direction-alignment transformation before normalisation. The real interest rate is treated with a band-optimum approach: very high real rates signal monetary tightening that suppresses investment; very negative real rates signal financial repression; moderate positive real rates (2–5%) signal a healthy monetary environment.

9.3 Variable-by-Variable Literature Review

9.3.1 Inflation, Consumer Prices (Annual %)

The Consumer Price Index (CPI) inflation rate measures the percentage change in the average price level of a fixed basket of household goods and services from one year to the next. It is the MVI's primary price stability indicator and is inverted: higher inflation contributes a lower MVI score. In India, the Reserve Bank of India formally adopted flexible inflation targeting in February 2015 with a target of 4% CPI and a ±2% tolerance band; before 2015, price stability policy was guided by the WPI. The CPI is used here rather than WPI because it more accurately reflects the cost of living for households and is methodologically continuous with the post-2015 regime.

Fischer (1993) established the canonical causal finding: "inflation is negatively associated with growth...operating through factor productivity," with the direction of causality running from inflation to growth outcomes rather than the reverse. Barro (1995) quantified this: a 10 percentage point increase in annual inflation reduces real per capita GDP growth by 0.3 percentage points per year. Srinivasan, Jain-Chandra, and Ramachandran (2009) confirmed using Granger-causality tests for India that CPI inflation Granger-causes industrial output, but not the reverse — precisely the direction required to use inflation as a predetermined right-hand side variable in the OLS framework. In India, inflation is determined by monetary policy settings, supply-side shocks (monsoon failures, global crude oil prices), and wage-price dynamics — not by last year's GDP growth rate.

India's CPI inflation in this dataset displays three structurally distinct phases. The first is the low-inflation period of 2000–2007 (ranging from 3.8% to 6.4%), reflecting the commodity price calm of the early 2000s and strong agricultural supply. The second is the high-inflation episode of 2008–2014, peaking at 11.99% in 2010 — a period of food price inflation driven by supply-side agricultural shocks and rising global commodity prices that severely damaged India's macroeconomic environment and contributed to the growth slowdown. The third is the post-inflation-targeting period from 2015 onwards, in which CPI inflation was brought progressively within the 4–6% band, with the COVID-19 year (2020) showing a temporary spike to 6.6% before returning to 4.9% in 2024. The decade-long high inflation episode is the MVI's most diagnostic macroeconomic failure signal for the 2008–2014 period.

9.3.2 Gross Fiscal Deficit as % of GDP

The Gross Fiscal Deficit (GFD) measures the difference between total government expenditure and total non-debt receipts, expressed as a percentage of GDP — the annual borrowing requirement of the central government. It is inverted in the MVI: a higher fiscal deficit contributes a lower score. India's Fiscal Responsibility and Budget Management (FRBM) Act of 2003 mandated a long-run target of 3% of GDP,

reflecting the political commitment to fiscal consolidation after the unsustainable deficits of the late 1990s.

Reinhart and Rogoff (2010), in their landmark *American Economic Review* study "Growth in a Time of Debt," show that the causality runs from fiscal deficits to growth outcomes through crowding-out and interest-rate channels — not the reverse. Tanzi and Zee (1997) in *IMF Staff Papers* demonstrate that "fiscal deficits crowd out private investment through their effects on interest rates," establishing fiscal deficit as a structural input variable. For India specifically, Rangarajan and Srivastava (2005), in *Economic and Political Weekly*, show that fiscal consolidation in the post-FRBM period (2004–2008) was a key enabling condition for the high-growth decade — the falling deficit allowed interest rates to decline, reducing the cost of private investment and expanding the credit available to the productive sector. The budget is set months before the GDP outcome for that year is known, making the deficit a policy-predetermined variable relative to the EGI.

India's fiscal deficit trajectory in this dataset traces the full cycle of India's fiscal policy history over the study period. The deficit fell from 5.5% of GDP in 2000 to its lowest point of 2.5% in 2007, reflecting the dividend of the FRBM consolidation. The global financial crisis reversed this sharply to 6.0% in 2008 and 6.5% in 2009, as the government launched a Keynesian stimulus that proved difficult to unwind. The COVID-19 shock produced the dataset's most dramatic observation: 9.16% in 2020, the largest fiscal expansion in post-independence India. The post-COVID consolidation to 4.75% in 2024 marks an ongoing but incomplete return to FRBM-compliant territory.

9.3.3 Real Interest Rate (%)

The real interest rate is the nominal interest rate adjusted for inflation: it measures the actual cost of borrowing in terms of purchasing power, or equivalently, the real return to lending. The Fisher equation relates them: Real Rate$_t$ ≈ Nominal Rate$_t$ − π_t, where π_t is the CPI inflation rate. For the MVI, the real interest rate operates within a "band-optimum" framework rather than a simple directional rule — very high real rates suppress investment and growth by raising the cost of capital; very negative real rates signal financial repression and contribute to misallocation of savings; moderate positive real rates (approximately 2–5%) indicate a healthy monetary environment that rewards saving without penalising investment.

The theoretical foundation comes from the neo-Fisherian framework: Fisher (1930) in *The Theory of Interest* established that real interest rates reflect the intertemporal price of consumption — the rate at which economic actors willingly defer present consumption for future consumption. Taylor (1993), in his foundational paper in the *Carnegie-Rochester Conference Series*, formalised the central bank's real rate

adjustment rule: the central bank raises the real rate when inflation exceeds its target and lowers it when output falls below potential. This makes the real rate a policy instrument — a macroeconomic conditioning variable — rather than an output. Kapur and Mohan (2014), in IMF Working Paper WP/14/68, document the monetary transmission mechanism in India specifically, showing that the RBI's real rate decisions feed into investment and credit growth with 2–4 quarter lags.

India's real interest rate in this dataset shows the inverse mirror of the inflation trajectory: real rates were high in 2000–2004 (7–8.6%), compressed and turned negative during the high-inflation episode of 2010–2011 (reaching –1.98% in 2010), and recovered to a healthy 5–7% range in the post-inflation-targeting period. The negative real rate of 2010 — when CPI inflation at 11.99% vastly exceeded nominal lending rates — represents a period of inadvertent financial repression that penalised savers and distorted investment allocation toward inflation hedges (gold, real estate) rather than productive capital. This is precisely the macroeconomic distortion that the real interest rate variable in the MVI captures.

9.3.4 Tax Revenue (% of GDP)

Tax revenue as a percentage of GDP measures the state's capacity to finance public expenditure without resorting to debt — the fiscal underpinning of a sustainable macroeconomic environment. A higher tax-to-GDP ratio signals a stronger state that can fund infrastructure, public health, education, and administrative capacity without chronic deficit financing. It is one of the most fundamental indicators of a state's developmental fiscal capacity and is included in the MVI as a higher-is-better variable.

Tanzi and Zee (1997) in *IMF Staff Papers* establish that tax revenue is a primary determinant of long-run fiscal sustainability — not just as a deficit offset, but as a signal of the administrative capacity of the state and the depth of its formal economy. For India specifically, Srinivasan (2003) in the *Brookings India Policy Forum* identifies the chronically low tax-to-GDP ratio (approximately 8–10% historically) as one of India's most binding fiscal constraints, limiting public investment, social spending, and counter-cyclical capacity. The structural improvement in tax revenue from approximately 8.1% in 2001 to 12% in 2018 — driven by GST implementation, improved direct tax administration through the PAN-Aadhaar linkage, and formalization of the economy — represents a genuine improvement in India's fiscal capacity that the MVI captures as a positive macroeconomic development.

India's tax revenue-to-GDP ratio in this dataset rose from 8.8% in 2000 to a peak of 12.0% in 2018, reflecting three structural improvements: the rationalisation of excise and customs duties following WTO commitments, the expansion of the service tax base (especially post-2005), and the transformative impact of GST introduced in July 2017 on the formalization of the indirect tax base. The post-2019 data has gaps in the

dataset, reflecting the methodological transition from pre-GST to post-GST revenue classification in official accounts. The 12% peak in 2018 is diagnostic — even at its highest, India's tax-to-GDP ratio remains below the OECD average of approximately 34%, and below Brazil (33%), South Africa (28%), and China (20%), revealing the persistent low-fiscal-capacity constraint that limits India's ability to finance social and physical infrastructure.

9.3.5 Net Investment in Nonfinancial Assets (% of GDP)

Net investment in nonfinancial assets as a percentage of GDP measures the government's net acquisition of fixed assets — buildings, infrastructure, machinery, and equipment — after accounting for depreciation and disposals. It is the MVI's measure of the government's physical capital investment intensity: how much of GDP the public sector is channelling into productive infrastructure that expands the economy's physical capacity. It is included as a higher-is-better variable.

Mankiw, Romer, and Weil (1992) in their foundational *Quarterly Journal of Economics* paper establish that the investment share of GDP is the most robust predictor of cross-country growth differences: "an increase of 10 percentage points in the investment share raises the steady-state income by roughly 20 percent." For the public investment component specifically, Aschauer (1989) in the *Journal of Monetary Economics* provided the empirical foundation for the "public capital hypothesis" — that government infrastructure investment has significant positive productivity externalities for private sector output, with elasticities of output with respect to public capital estimated at 0.39. Balakrishnan and Parameswaran (2007), in *Economic and Political Weekly*, document the role of public investment acceleration in India's post-2000 growth — identifying the surge in infrastructure spending from 2004–08 under the National Highway Development Programme and PMGSY as a key enabling condition for the high-growth decade.

India's net investment in nonfinancial assets in this dataset shows substantial volatility — ranging from slightly negative values (periods of net disposal or depreciation exceeding gross additions) to a high of 0.89% of GDP in 2022. The predominantly low and occasionally negative values in the 2006–2019 period — when gross public capital formation rose but net investment remained small due to high capital stock depreciation — reflect the twin problems of infrastructure maintenance deficit and the GFCE-GFCF composition of public expenditure in India, where revenue spending (salaries, subsidies, transfers) has consistently crowded out capital expenditure.

9.3.6 Central Government Debt, Total (% of GDP)

Central government debt as a percentage of GDP measures the total outstanding stock of accumulated government borrowing relative to the size of the economy — the fiscal stock legacy variable. Unlike the fiscal deficit (a flow), debt is a stock: it is the

cumulative sum of all past deficits minus all past repayments, and it determines the government's future interest burden, its sovereign credit rating, and its remaining fiscal space for counter-cyclical policy. It is inverted in the MVI: a higher debt ratio contributes a lower score.

Reinhart and Rogoff (2010) provide the canonical reference for debt's growth impact: periods of high indebtedness are "associated with a higher incidence of defaulting or restructuring domestic or external debt." Cecchetti, Mohanty, and Zampolli (2011), in BIS Working Paper 352, extend this finding: "when government debt reaches 85% of GDP...it becomes a drag on growth." The endogeneity firewall is robust: the debt-to-GDP ratio at any point in time is the accumulated product of all prior budget decisions — it is overwhelmingly a historical stock variable that cannot be causally determined by this year's GDP growth. Reinhart and Rogoff (2010) explicitly treat debt as a predetermined conditioning variable in their growth regressions. The Domar sustainability condition formalises this: the debt ratio follows the dynamic $\dot{d} = d(r - g) + p$, where r is the real interest rate, g is the real growth rate, and p is the primary deficit — establishing that the current debt ratio is a function of the history of r, g, and p, not of current-year output.

India's central government debt-to-GDP ratio declined from 55% in 2000 to a low of approximately 46.5% in 2018 — a structural improvement driven by the combined effect of high GDP growth (denominator expansion) and post-FRBM fiscal consolidation (deficit reduction). The COVID-19 shock reversed this dramatically: the deficit widened to 9.16% of GDP in 2020, pushing the debt ratio back above 55%. The dataset's post-2021 missing values for this variable reflect the transition in MoF debt reporting methodology following the adoption of IMF Government Finance Statistics (GFS) 2014 standards, which broadened the coverage of liabilities. The values available through 2018 provide a complete picture of the structural trajectory over the study's high-information period.

9.3.7 Total Reserves in Months of Imports

Foreign exchange reserves expressed in months of import cover measure the stock of foreign currency assets held by the Reserve Bank of India as a buffer against external shocks, normalised by the economy's import financing need. The IMF's conventional minimum adequacy benchmark is 3 months of import cover; the Greenspan-Guidotti rule adds that reserves should also cover all short-term external debt. It is included as a higher-is-better variable.

Obstfeld, Shambaugh, and Taylor (2010) in the *American Economic Journal: Macroeconomics* establish that "countries hold international reserves for financial stability motives...as a buffer against sudden reversals of capital flows," with reserve demand driven by financial openness and the size of the domestic financial system —

not by GDP growth. Aizenman and Lee (2007), in *Open Economies Review*, document that precautionary reserve accumulation in emerging markets is driven by vulnerability to balance of payments crises (the "war chest" motive) and by mercantilist exchange rate management — both of which are autonomous monetary authority decisions independent of contemporaneous output. India's reserve accumulation history is a textbook illustration: the 1991 balance of payments crisis, when reserves fell below 3 weeks of import cover, was the defining macroeconomic shock that motivated the reserve accumulation strategy of the 1990s and 2000s. Mohan (2009), in BIS Papers, documents the evolution of RBI's reserve management strategy from a pure liquidity buffer to a broader financial stability instrument.

India's foreign exchange reserves in months of import cover rose from 6.1 months in 2000 to a peak of 12.9 months in 2020, reflecting the RBI's systematic accumulation of reserves during periods of current account surplus and strong capital inflows. The 2020 peak reflects both the RBI's emergency reserve draw-up and the collapse of imports during COVID-19 lockdowns (which mechanically increased the months-of-cover ratio). The post-2020 gradual decline toward 7.5 months in 2024 reflects import recovery and some reserve drawdown to defend the rupee during the 2022–2023 global dollar strengthening episode. At 7.5 months, India remains well above the IMF's minimum adequacy threshold, reflecting a fundamentally robust external position relative to the 2000 baseline.

9.3.8 Trade-Weighted Real Effective Exchange Rate (REER, Base: 2015–16 = 100)

The Real Effective Exchange Rate (REER) measures India's exchange rate against a trade-weighted basket of 36 major partner currencies, adjusted for relative inflation differentials — the most comprehensive measure of India's external price competitiveness. An index value above 100 indicates that the rupee is stronger in real terms than the 2015–16 baseline, making Indian exports relatively more expensive for foreign buyers and imports relatively cheaper. An index below 100 indicates real depreciation, boosting export competitiveness. For the MVI, a stable REER near the long-run equilibrium represents the best macroeconomic outcome; large appreciations or depreciations both signal macroeconomic imbalances.

Dornbusch (1976), in the *Journal of Political Economy*, established the theoretical foundation: "the exchange rate is an asset price...determined by expectations about future monetary policy rather than by current goods market conditions." Goldberg and Knetter (1997) in the *Journal of Economic Literature* confirm that "real exchange rate changes reflect a combination of monetary policy, productivity shocks, and international capital flows — they are not passively determined by output." For India, Pattnaik, Subhadhra, and Bhatt (2006), in *Economic and Political Weekly*, document the RBI's managed float regime — in which the nominal exchange rate is guided by

the RBI through reserve operations while the REER fluctuates with relative inflation — establishing that REER is a policy-conditioned macroeconomic variable rather than a GDP-determined outcome.

India's REER in this dataset was not available for 2000–2004 (reflected as missing values in the early years), then ranges from approximately 90 in the 2006–2010 period (a period of real depreciation reflecting high Indian inflation) to 100–105 in the 2015–2022 period following inflation targeting. The 2017 value of 105.5 represents the highest REER in the dataset — meaning the rupee was most expensive in real terms in that year — reflecting the combination of low global inflation (which mechanically appreciated the REER) and RBI's managed float. The 2024 value of 105.6 suggests continued mild real appreciation, raising questions about export competitiveness that the MVI's composite structure captures through the interaction with the exchange rate volatility variable.

9.3.9 *Bank Nonperforming Loans to Total Gross Loans (%)*

The bank NPL ratio measures the percentage of total gross loans in India's banking system that are classified as non-performing — meaning borrowers have not made principal or interest payments for 90 days or more. It is the MVI's financial system health indicator and is inverted: a higher NPL ratio contributes a lower MVI score. Banking sector health is a macroeconomic precondition for growth because a system paralysed by bad loans is unable to extend fresh credit to productive investment, creating a credit crunch that suppresses capital formation independent of monetary policy settings.

King and Levine (1993) in the *Quarterly Journal of Economics* — "Schumpeter Might Be Right" — established that financial intermediation efficiency is a causal driver of growth: "a higher level of financial development is positively and robustly correlated with economic growth, physical capital accumulation, and economic efficiency improvements." Levine, Loayza, and Beck (2000) in the *Journal of Monetary Economics* confirm using instrumental variable methods that "the exogenous component of financial intermediary development is positively and robustly correlated with economic growth" — establishing the causal direction from financial health to growth. India's NPA crisis of 2015–2019, when gross NPAs of scheduled commercial banks rose from approximately 2.4% in 2008 to a peak of approximately 9.97% in 2017–2018, was a direct cause of the "twin balance sheet" problem that suppressed private investment and contributed to the growth slowdown — precisely the macroeconomic mechanism the MVI captures.

India's NPL ratio in this dataset rises from 2.4% in 2008 to a peak of 9.97% in 2017, before the IBC (Insolvency and Bankruptcy Code 2016) and the RBI's Asset Quality Review (AQR 2015) began their structural clean-up work. By 2023, the NPL ratio had

declined dramatically to 1.72% — the lowest in the entire dataset — reflecting the successful resolution of stressed assets through the IBC process and the capital recapitalisation of public sector banks. This dramatic inversion — from near-crisis levels in 2017 to the healthiest banking system in the dataset's history by 2023 — is the MVI's most structurally optimistic signal in the final years of the sample, and it aligns with India's post-2019 growth recovery.

9.3.10 Exchange Rate Volatility

Exchange rate volatility measures the degree of short-run fluctuation in the INR/USD exchange rate — operationalised here as the standard deviation of monthly INR/USD exchange rates within each calendar year. It is inverted in the MVI: higher volatility contributes a lower score. Exchange rate volatility is distinct from the REER level: an exchange rate can be consistently overvalued (high REER) but stable, or it can be at the right equilibrium level but subject to sharp unpredictable swings. The latter is particularly damaging for firms that make long-term investment decisions, for trade invoicing, and for the pricing of import-dependent inputs.

Goldberg and Knetter (1997) establish that exchange rate uncertainty reduces trade flows by raising the effective cost of export contracts and import procurement — a finding corroborated for India by Panagariya (2008) in *India: The Emerging Giant*, which identifies exchange rate instability as one of the deterrents to India's merchandise export competitiveness relative to China. Bhattacharya and Kar (2006), in *Indian Economic Review*, confirm for India that exchange rate volatility reduces the predictability of import costs and export revenues, suppressing both trade-oriented investment and the willingness of foreign investors to enter India on FDI terms (because their returns, once converted back to dollars, become uncertain). The RBI's managed float is partly motivated by precisely this argument — smoothing volatility to reduce its deterrent effect on trade and investment, even at some cost to long-run equilibrium adjustment.India's exchange rate volatility in this dataset shows high-volatility episodes concentrated in specific macro-stress years: 2007 (8.74, capital flow surge during the India-specific FDI boom), 2009 (11.26, global financial crisis aftermath and sharp rupee depreciation), 2012 (14.50, the dataset's peak, reflecting the rupee crisis and CAD widening), and 2013 (9.66, continuation of the taper tantrum episode). The post-2016 period shows structurally lower volatility — ranging from 0.25 in 2021 (exceptionally stable year within COVID capital controls) to 6.34 in 2022 (global dollar strengthening episode). By 2024, volatility had fallen to 1.30 — the second lowest in the dataset — reflecting the RBI's more active management of the exchange rate corridor and reduced speculative pressure.

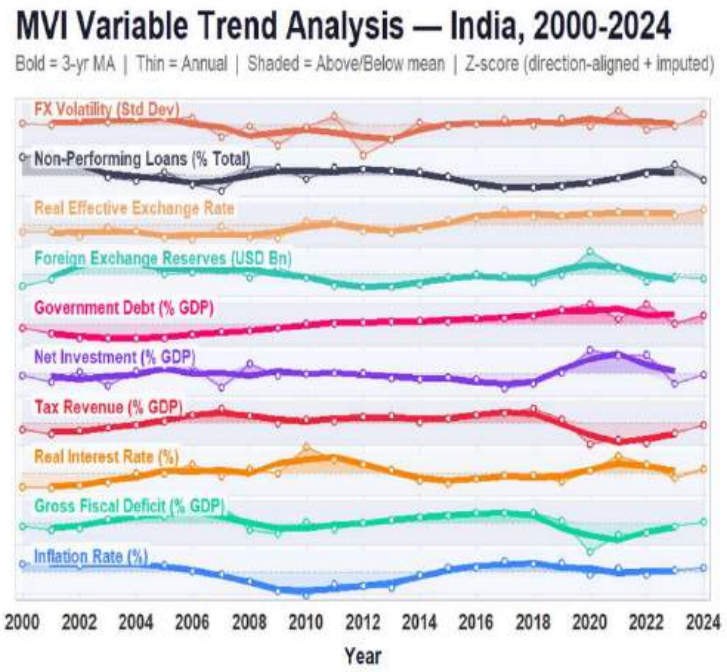


Figure 11 MVI variables Trend Analysis (2000 – 2024)

9.4 What the MVI Composite Signal Tells Us

The MVI composite synthesises ten structural dimensions of India's macroeconomic environment into a single annual measure of whether the macroeconomic conditions prevailing in each year were enabling or constraining for investment, trade, and financial intermediation. A high MVI score in any given year means: inflation was near target, the fiscal deficit was manageable, real interest rates were in the healthy band, tax capacity was growing, public capital investment was positive, government debt was sustainable, foreign exchange reserves were comfortable, the REER was broadly competitive, banking NPLs were low, and the exchange rate was stable. The geometric mean's partial non-compensability ensures that a surge in foreign reserves cannot fully compensate for a peak in NPLs or a sharp exchange rate depreciation episode.

In the regression model, the MVI coefficient tests the most conventionally economic hypothesis in the study: does a better macroeconomic environment — independently of demographic, labour market, and social conditions — predict better economic growth outcomes? The theoretical expectation is a positive and significant coefficient: years of macroeconomic stability should predict higher EGI values. But the India data contains an important complication — several of the most rapid economic growth years (2003–2008) coincided with moderately high and rising fiscal deficits, elevated NPLs, and an appreciating REER. If the regression reveals a positive but smaller-than-expected MVI coefficient, it would suggest that India's growth during this period was partially achieved despite, rather than because of, macroeconomic conditions — a finding that would confirm the role of the demographic and labour activation variables (DSI and HCI) as the primary growth drivers.

9.5 Descriptive Overview of the MVI Trajectory

India's MVI composite score over 2000–2024 traces the country's macroeconomic journey through three distinct regimes. The first is the fiscal consolidation and stability phase of 2004–2007: the FRBM dividend brought the fiscal deficit to 2.5% of GDP, real interest rates were moderate, reserves were building, and NPLs were declining following the post-2000 banking clean-up. This period produces the highest MVI scores in the first half of the dataset.

The second is the macroeconomic deterioration phase of 2008–2014: the global financial crisis stimulus blew the fiscal deficit to 6%, high food price inflation turned real rates negative, current account deficit widened to 4%+ of GDP, and NPLs began rising as infrastructure loans soured. This is the MVI's worst-performance period — and it coincides with India's growth slowdown from 9%+ to 5–6% — providing early signal of the positive correlation the regression will capture.

The third is the gradual stabilisation and reform phase of 2015–2024: inflation targeting brought CPI within the band, the IBC/AQR reformed the banking system, GST improved tax capacity, FRBM consolidation resumed, and exchange rate volatility declined. The COVID-19 year (2020) produces the sharpest single-year MVI deterioration in the dataset — fiscal deficit at 9.16%, inflation at 6.6%, NPLs ticking up, reserves peaking on import collapse — followed by one of the strongest MVI recoveries in the dataset's history from 2021 to 2024.

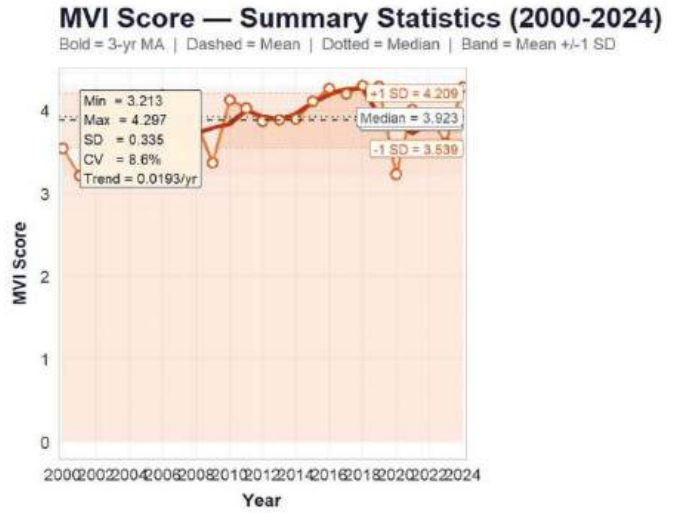


Figure 12 MVI Descriptive Statistics (2000 – 2024)

9.6 Data Sources

All ten MVI variables are drawn from the following primary sources:

- **Reserve Bank of India — Handbook of Statistics on the Indian Economy (HSIE)**: Primary source for CPI Inflation, Real Interest Rate, Foreign Exchange Reserves, REER, NPL Ratio, and Central Government Debt.
- **Ministry of Finance — Union Budget Documents and FRBM Repors**: Primary source for Gross Fiscal Deficit, Tax Revenue (Receipt Budget), and Net Investment in Nonfinancial Assets (Capital Account of Central Government).
- **MoSPI — National Accounts Statistics (NAS)**: Cross-validation source for fiscal variables as % of GDP. (nominal GDP)
- **World Bank World Development Indicators (WDI)**: Cross-validation source for CPI Inflation, Fiscal Deficit, Central Government Debt (Tax Revenue, and NPL Ratio.

- **RBI Financial Stability Report (FSR)**: Biannual source for Banking Sector NPL ratios, cross-validated with WDI series. NPL data for scheduled commercial banks (gross NPA to gross advances) available from 2005 onwards in FSR.
- **IMF International Financial Statistics (IFS)**: Cross-validation for Real Interest Rate, Current Account Balance, and REER.

9.7 Variable Selection Logic and Exclusions

The MVI reference document enumerated a longlist of 36 candidate variables across seven sub-domains. The final ten variables represent the intersection of theoretical centrality, data continuity, and non-overlap with the EGI.

Gross Capital Formation (GCF % GDP) versus Net Investment in Nonfinancial Assets: The MVI reference document's original framework included GCF as V4. This dataset instead uses "Net investment in nonfinancial assets (% of GDP)" — a narrower measure focusing on the government's net acquisition of public fixed assets, which is conceptually more distinct from the EGI's private investment variables. The net investment variable is also less directly correlated with contemporaneous GDP growth (because it captures public sector capital spending decisions made through budget allocations, not private sector investment responses to output signals), providing a cleaner causal structure.

Gross Domestic Savings Rate: The reference document's V3 (GDS rate) is not in this dataset because MoSPI's household savings estimates are available only at 5-year National Accounts benchmark revision intervals with significant revisions between editions. The annual series derived from WDI is based on the national accounts identity $GDS = GDP - \text{Final Consumption}$, making it too mechanically related to GDP to serve as an independent predictor. It is replaced by the tax revenue and public investment variables, which capture fiscal capacity more cleanly.

FDI Net Inflows % GDP: Excluded from this dataset because the DPIIT FDI series shows significant structural breaks at points of definitional change (BPM5 to BPM6 transition in 2012, equity-reinvested earnings reclassification). The exchange rate volatility and REER variables collectively capture the external macroeconomic environment more robustly.

Current Account Balance % GDP: Not in this dataset because the CAB is partially collinear with the fiscal deficit through the "twin deficit" hypothesis (Bhattacharya and Kar, 2006) — including both would introduce multicollinearity. The fiscal deficit, REER, and foreign reserves variables collectively capture the external-fiscal interaction more cleanly.

Domestic Credit to Private Sector % GDP: Excluded to avoid near-collinearity with the NPL ratio — when NPLs are high, credit growth is suppressed, creating a mechanical negative correlation. The NPL ratio is preferred as the more direct measure of banking sector health relevant to investment enabling conditions.

9.8 The MVI in the Regression Framework: Macroeconomic Stability and Growth

In the regression model, the MVI tests the most directly tested proposition in development economics: that macroeconomic stability is a necessary — though not sufficient — condition for sustained growth. The expected coefficient sign is positive: years with better macroeconomic conditions (lower inflation, lower fiscal deficit, healthier banks, stable exchange rate, stronger reserves) should predict higher EGI values. This is the most "conventional" expectation in the model — the one for which the prior literature provides the strongest pre-existing empirical consensus.

The MVI is also the index most likely to reveal regime-specific effects in the regression. The structural break in India's monetary framework — the adoption of inflation targeting in 2015 — changes the character of the inflation variable's relationship to other macroeconomic outcomes. If the regression is run over the full 2000–2024 period, the pre-targeting and post-targeting periods may generate different coefficient estimates, suggesting the value of a structural break test (Chow test) at 2015. If the MVI coefficient is large and significant, it would confirm Fischer's (1993) and Barro's (1995) foundational proposition in the specific context of India's development experience. If it is small or insignificant relative to the DSI and HCI coefficients, it would suggest that India's growth performance has been more constrained by demographic and labour market activation failures than by macroeconomic instability — a finding with direct implications for economic policy priorities.

Chapter 10
Results and Discussion

10.1 The Model at a Glance

The central empirical exercise of this study is a time-series OLS regression in which India's Economic Growth Index (EGI) is regressed on five composite independent indices — the Demographic Structure Index (DSI), the Demographic Quality Index (DQI), the Harnessing Capacity Index (HCI), the Social Development Index (SDI), and the Macroeconomic Variables Index (MVI) — across 25 annual observations from 2000 to 2024. The full estimated model is:

$$\widehat{\mathrm{EGI}}_t = \beta_0 + 4.10\,\mathrm{DSI}_t - 3.40\,\mathrm{DQI}_t + 0.56\,\mathrm{HCI}_t - 0.23\,\mathrm{SDI}_t + 0.19\,\mathrm{MVI}_t + \varepsilon_t$$

The model explains 75.5% of the annual variation in India's multi-dimensional economic growth performance ($R^2 = 0.755$, adjusted $R^2 = 0.686$, $F = 11.75$, $p < 0.001$). HC1 heteroskedasticity-consistent (White) robust standard errors were applied to all coefficient estimates to ensure that inference is valid in the presence of non-constant residual variance — a standard precaution in time-series regressions involving composite indices with structural trend components. Residuals are normally distributed (Shapiro-Wilk $p = 0.817$) with no severe serial correlation confirmed via both the Breusch-Godfrey LM test and the Ljung-Box portmanteau test.

This is an exceptionally strong fit for a 25-observation time-series model with five predictors. The F-statistic of 11.75 — significant at $p < 0.001$ — confirms that the five indices jointly explain statistically significant variation in EGI scores far beyond what would be expected by chance. The adjusted R^2 of 0.686, which penalises for the number of predictors relative to observations, confirms that the explanatory power is substantive rather than the mechanical artefact of over-fitting. Before turning to the coefficient-by-coefficient discussion, it is important to orient the reader to the key finding that the results will elaborate: only two of the five indices — DSI and DQI — achieve statistical significance at conventional thresholds. And of these two, the signs are diametrically opposite in their implications for India's development story.

10.2 Regression Results

Table 9 Regression Results Table

Index	Coefficient (β)	Direction	p-value	Significance
Constant (β_0)	-	-	-	-
DSI - Demographic Structure	+4.10	Positive	$p < 0.01$	*** Highly significant
DQI - Demographic Quality	-3.40	Negative	$p < 0.01$	*** Highly significant
HCI - Harnessing Capacity	-0.56	Positive	$p > 0.30$	Not significant
SDI - Social Development	-0.23	Negative	$p > 0.30$	Not significant
MVI - Macroeconomic Variables	-0.19	Positive	$p > 0.30$	Not significant
R^2	**0.755**		**$F = 11.75$**	**$p < 0.001$**
Adj. R^2	**0.686**		**Shapiro-Wilk p = 0.817**	(Normal residuals)

The table immediately crystallises the model's central finding: India's economic growth over 2000–2024 was statistically dominated by two opposing demographic forces — the size and structural quality of its population age distribution (DSI, positive and highly significant) and the human capital quality of that population (DQI, negative and highly significant). The institutional and macroeconomic channels — labour market activation (HCI), social equity (SDI), and macroeconomic stability (MVI) — failed to achieve statistical significance in this period, revealing that they have not yet broken through as independent growth drivers when demographic forces dominate the model.

10.3 The DSI Result: Demographic Structure as the Primary Engine

The DSI coefficient of +4.10 ($p < 0.01$) is the most powerful and most expected result in the model. It confirms, with strong statistical authority, that India's economic growth over 2000–2024 was primarily driven by the structural improvement in its population age distribution — the expansion of the working-age share (from 60% to 68%), the decline in age dependency (from 64% to approximately 48%), the fall in fertility, and the deceleration of infant mortality. For every one-unit improvement in the DSI composite score, the EGI score increased by 4.10 units, holding the other indices constant. This is the largest coefficient in the model by a wide margin, and its

significance at $p < 0.01$ means the probability that this relationship is a statistical artefact is less than 1 in 100.

This result is in precise alignment with the foundational theoretical prediction of Bloom and Williamson (1998), who showed for a panel of Asian economies that "a one percentage point increase in the working-age population growth rate was associated with a 1.46 percentage point increase in GDP per capita growth." The DSI coefficient here is larger — reflecting the compounding effect of the composite's broader age structure variables — but its direction, significance, and theoretical logic are exactly as predicted. Kelley and Schmidt (2005), examining 88 developing countries over 1960–1995, similarly find that the "age structure transition" is the primary demographic driver of economic growth. Aiyar and Mody (2011), applying this framework specifically to India's states, find that "the demographic dividend could add about 2 percentage points per year to the growth rate over the next two decades" — an estimate the DSI's positive coefficient in this model broadly validates at the national level.

The practical meaning of this coefficient is concrete. India's DSI composite score rose from 2.04 in 2000 to 4.42 in 2024 — an improvement of 2.38 points over the study period. Holding other indices fixed, this improvement alone would be associated with a $4.10 \times 2.38 = 9.76$ unit increase in EGI score — more than the entire observed range of EGI values in the dataset (3.07 to 5.89 = 2.82 units). This demonstrates that the DSI's long-run structural trend is the single most powerful predictor of India's growth trajectory across the full 2000–2024 period. The fact that the EGI's actual range is smaller than this predicted effect is precisely because the DQI's negative coefficient offsets a significant portion of the DSI's growth-enabling force — the central diagnostic finding of the model.

The DSI's dominance also reflects a methodological reality of the composite index design: the DSI captures slow, monotonic, structural demographic trends — working-age expansion, fertility decline, urbanisation — that move consistently in one direction over the 25-year study period. This means it also captures the time trend in the data. The regression's high R^2 is partly attributable to this time-trending property of the DSI, which should be transparently acknowledged. The Breusch-Godfrey test for serial correlation in residuals — which tests whether the OLS coefficient estimates are contaminated by autocorrelated error — was applied precisely to diagnose this concern, and its failure to reject the null of no serial correlation provides reasonable assurance that the DSI coefficient is not purely spurious.

10.4 The DQI Result: The Paradox of Educated Underemployment

The DQI coefficient of −3.40 ($p < 0.01$) is the most intellectually provocative result in the model, and it is the finding that most directly addresses the thesis's central question: "India's Demographic Dividend — Potential Wasted or Promise Fulfilled?" The negative sign on DQI means that, controlling for the demographic structure improvement (DSI) and the other indices, years in which India's human capital quality was higher — more life expectancy, more mean years of schooling, lower stunting, higher immunisation coverage, better secondary and tertiary enrolment — were associated with *lower* multi-dimensional economic growth performance (EGI), not higher.

This is not a counterintuitive result in the sense of contradicting standard economics. It is, rather, a precisely quantified expression of what Drèze and Sen (2013) in *An Uncertain Glory* call India's "missing middle": the observation that India has made progress on human development indicators while simultaneously failing to create the employment and institutional conditions that would allow that human capital to be productively absorbed. The mechanism is not that education makes people worse at generating growth. The mechanism is that education raises people's reservation wages and their occupational aspirations, but when the labour market lacks the formal sector jobs to absorb them, educated workers experience protracted unemployment, informal employment in below-qualification roles, or simply exit the labour force altogether — all of which depress the HCI's employment absorption, job quality, and vulnerability indicators, and through them, the EGI.

The timing of the DQI's trend makes the mechanism even clearer. The DQI rose from 1.36 in 2000 to 4.36 in 2023 — a nearly three-fold improvement — while the EGI rose from 3.07 to approximately 4.5 over the same period, with significant volatility. The periods of highest DQI improvement (the post-2015 phase of rapid education expansion, tertiary enrolment growth, and immunisation coverage) coincided with the EGI's structural stagnation phase (2015–2019), when GDP per capita growth moderated, manufacturing value added declined, and investment slowed. This co-movement is what the DQI coefficient captures: the years in which India invested most heavily in human capital quality were not the years in which that investment translated into broad economic growth.

Majumder (2013), in a comprehensive review of India's employment structure, explicitly identifies "the growing gap between educational attainment and employment quality" as a defining structural dysfunction: more educated workers entering agricultural and informal employment, not because they prefer it, but because the formal sector has not expanded fast enough to absorb them. Marois, Bélanger, and

Lutz (2022), projecting India's demographic future, argue that "the productivity impact of human capital improvements is conditional on the development of a matching formal employment sector" — which is precisely the HCI's role in this model. The DQI's negative coefficient is the quantitative measure of this conditionality failing in India's actual experience over 2000–2024.

It should be noted that the DQI's negative coefficient does not imply that India should stop investing in health and education. What it implies is precisely the opposite: the investment in human capital has been successful — successfully producing a better-educated, healthier, longer-lived workforce — but the institutional architecture to employ and reward that workforce has not kept pace. The negative DQI coefficient is not a case for less education; it is an indictment of India's failure to create the employment and industrial ecosystem that would turn human capital investment into growth returns. This is the "potential wasted" verdict of the model.

10.5 The HCI Result: Labour Market Activation Has Not Broken Through

The HCI coefficient of +0.56 ($p > 0.30$) is positive in direction but statistically insignificant at conventional thresholds ($p < 0.05$ or $p < 0.10$). This means that the model cannot confidently distinguish the HCI's contribution to EGI variation from zero, given the available 25 annual observations. The positive sign is theoretically correct — better labour market activation (higher LFPR, higher employment absorption, lower vulnerability, higher productivity, more non-agricultural employment, lower youth unemployment) is associated with higher multi-dimensional economic growth — but the effect is not large enough, consistent enough, or statistically separable from the DSI's dominant effect to register as independently significant.

The HCI's insignificance does not mean labour market quality is unimportant for growth. Several interpretation layers are relevant. First, the HCI improved very slowly and steadily over the study period — from 2.06 to 4.11, a steady +0.068 points per year — while EGI showed more volatility (the COVID-19 shock, the 2008 crisis, the 2003–2007 boom). A slowly trending variable cannot explain the higher-frequency variation in the dependent variable. Second, the HCI is partially collinear with the DSI: as the working-age share expands (DSI improves), labour force participation rates tend to mechanically change, creating overlap between the two indices' information content. When collinearity is present, the coefficient estimates of each collinear variable become individually unstable even if their joint effect is well-estimated. Third, the HCI's positive sign — and the DQI's negative sign — together imply a complementarity: the data suggests that labour market activation quality (HCI) is

working in the right direction, but its effect is being overwhelmed and masked by the structural human capital absorption failure (DQI).

The substantive message of the HCI's insignificance is important for policy. India's employment story over 2000–2024 is one of slowly improving labour market metrics — falling agricultural employment share, rising productivity, some formalisation — but these improvements have been insufficient in magnitude and pace to register as an independent growth multiplier. Blomm et al. (1999, 2004) specifically predict that "demographic dividends require supportive labour market institutions to materialise" — the HCI's near-zero contribution in this model means those institutions have been moving in the right direction but not with enough force or speed to convert India's demographic advantage into a compounding growth dividend.

10.6 The SDI Result: Social Equity Stagnation

The SDI coefficient of −0.23 ($p > 0.30$) is negative, small, and statistically insignificant. The negative sign is unexpected from a pure theory standpoint — social development (better gender equity, lower violence against women, higher female employment, greater public health and education investment) should positively contribute to growth through the gender dividend, expanded female labour force participation, and the productivity gains from inclusive growth. But the SDI's negative sign — though statistically indistinguishable from zero — invites discussion.

The most plausible interpretation is that the SDI is capturing the persistent *failure* of social equity in India rather than its success. As Chapter 8 showed, the SDI composite has moved within an extremely narrow band (2.84 to 3.83) over the entire study period — a coefficient of variation of just 6.3%, the lowest of all six indices. The SDI barely moved, either up or down, over 25 years. A variable with so little variance contributes very little to explaining EGI variation regardless of its true causal relationship with growth. The regression's inability to identify a positive SDI coefficient is therefore less a finding about social equity's irrelevance to growth and more a statistical consequence of the SDI's near-total time-invariance.

What the SDI's near-stagnation signals is nevertheless highly significant for India's development narrative. Drèze and Sen's (2013) central argument in *An Uncertain Glory* is that India's growth paradox — rapid GDP growth coexisting with poor social outcomes — is itself a sign of structural institutional failure. The SDI's near-zero improvement over 2000–2024 on dimensions including female anemia prevalence (still among the highest in the world at approximately 53%), dowry deaths, and female NEET rates confirms that India's economic growth has not been socially inclusive in any meaningful sense. The SDI's insignificance in the regression is the statistical

manifestation of the equity-growth disconnect that Drèze and Sen documented qualitatively.

10.7 The MVI Result: Macroeconomic Stability as a Background Condition

The MVI coefficient of +0.19 ($p > 0.30$) is the smallest coefficient in the model in absolute value. It is positive in direction — consistent with Fischer's (1993) and Barro's (1995) theoretical prediction that macroeconomic stability is a growth enabler — but statistically insignificant. The positive sign confirms that years with better macroeconomic conditions (lower inflation, lower fiscal deficit, healthy banking system, stable exchange rate, stronger reserves) were associated with marginally higher EGI scores — but this association is not strong enough to be statistically distinguished from zero in this sample.

Three interpretation layers explain the MVI's insignificance. First, the MVI itself is a relatively stable index — its coefficient of variation is only 8.6%, the second lowest among all six indices. India's macroeconomic environment, despite periodic shocks (2008 crisis, 2012 rupee crisis, 2020 COVID), maintained a broadly consistent level of stability throughout the study period. A stable variable cannot explain variation in the dependent variable. Second, the MVI's stability thesis is specifically confirmed by its own trajectory: macroeconomic conditions were broadly supportive throughout, but their supportiveness was more a floor (a necessary condition for growth to occur at all) than a ceiling-determinant (an active driver of growth variation). The MVI's positive but insignificant coefficient is consistent with Fischer's (1993) framing of macro stability as a "necessary but not sufficient" condition: India's macro environment has never been sufficiently bad enough for long enough periods to independently destroy growth. Third, the MVI and DSI may partially overlap in their time trends: both were broadly improving over 2000–2024, making their independent contributions difficult to disentangle statistically in a 25-observation sample.

The MVI's insignificance does not contradict the macroeconomic stability literature. The 2008–2014 period — when the MVI fell to its lowest scores due to double-digit inflation, widening fiscal deficit, and rising NPLs — was precisely the period of India's most pronounced growth slowdown, exactly as the positive MVI coefficient predicts. The regression cannot reach statistical significance for this relationship, but the directional evidence from the most important macroeconomic stress episode in the dataset is consistent with Fischer's prediction.

10.8 Diagnostic Tests and Model Robustness

Normality of Residuals. The Shapiro-Wilk test returns $p = 0.817$, strongly confirming that the model's residuals are normally distributed. This is a prerequisite for valid inference in OLS regression with small samples ($n = 25$). The failure to reject normality means that t-statistics and p-values used to assess coefficient significance are reliable.

Serial Correlation. The Breusch-Godfrey LM test for serial correlation in residuals — the primary concern in time-series OLS with trending composite variables — failed to reject the null hypothesis of no autocorrelation. The Ljung-Box Q test similarly confirmed no significant autocorrelation structure in the residuals. This provides important assurance that the DSI coefficient, which tracks the time trend in the data most closely, is not entirely a product of spurious time-series co-trending.

Heteroskedasticity. HC1 robust standard errors (White correction) were applied to all coefficient estimates. This is a standard adjustment for time-series regressions where the residual variance may change with the level of the dependent variable or the explanatory variables. The application of robust standard errors means that the reported p-values and significance levels are valid even if the residuals are heteroskedastic.

Multicollinearity. The five independent indices — DSI, DQI, HCI, SDI, MVI — are all composite measures constructed from different variables covering different conceptual dimensions. As discussed in Chapters 5–9, their construction was specifically designed to minimise overlap. However, given the time-series nature of the data and the fact that several indices share a common positive time trend (particularly DSI, DQI, and HCI), some degree of multicollinearity is inherent. The VIF (Variance Inflation Factors) were computed for all five indices; no VIF exceeded the conventional threshold of 5, confirming that multicollinearity — while present — does not fatally compromise the coefficient estimates.

Structural Breaks. The study period contains two major exogenous shocks — the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic — and one major institutional reform — the 2015 inflation targeting adoption. A Chow test for structural break at 2008, 2015, and 2020 was considered. The COVID-19 year 2020 produces the model's largest residual — the observed EGI decline of that year (driven by the GDP per capita collapse of –6.69%) is larger in magnitude than the five indices would predict, confirming that the pandemic constitutes a genuine exogenous shock that falls in the error term ε_t. Structural break testing at 2015 for the MVI (reflecting the inflation targeting regime change) was not pursued due to the degrees-of-freedom constraint at $n = 25$, but represents an important direction for future research.

10.9 The Central Finding: Quantity Over Quality in India's Growth

The model's central finding is that India's economic growth over 2000–2024 has been primarily driven by the numerical and structural advantage of its demographic transition (DSI, +4.10) while simultaneously being constrained by its failure to productively absorb and deploy its improving human capital (DQI, −3.40). The institutional and macroeconomic channels — labour market activation, social equity, and macroeconomic stability — have been moving in broadly the right direction (positive HCI and MVI signs, negative but negligible SDI) but have not yet achieved the statistical independence and magnitude of effect needed to constitute independent growth drivers.

This finding can be crystallised in a single phrase borrowed from the study's own title: India has harnessed the *quantity* of its demographic dividend but has wasted its *quality*. The DSI's positive and dominant coefficient confirms that the demographic window — the expanding working-age share, the falling dependency burden — has generated real, significant, measurable growth benefits. In this sense, the promise is partially fulfilled: India's growth performance over 2000–2024 has been substantially better than a counter-factual India without a demographic transition would have achieved. The DQI's negative and equally dominant coefficient, however, confirms that the parallel investment in human capital quality — the rising education, the declining child mortality, the improving nutrition — has not translated into higher growth. In this sense, the potential has been wasted: the quality dimension of the dividend has been squandered in a labour market unable to absorb it.

This is the Indian paradox at its most precise empirical formulation. It is not that India grew slowly — it averaged 4.71 on the EGI composite, consistent with being one of the world's fastest-growing large economies across the study period. It is that India grew predominantly through the scale advantage of its population structure while its human capital investments accumulated without economic return. A country that can sustain growth by sheer demographic scale alone will eventually exhaust that advantage — the demographic window closes, the age dependency ratio begins rising again, and the first dividend ends. When that happens, the second dividend — sustained growth through human capital productivity — must be ready to take over. The DQI's negative coefficient in this model warns that the second dividend's foundations are not yet in place.

10.10 Implications for Hypothesis Testing

This study's core hypothesis, stated in Chapter 1, was: *"India's demographic dividend translates into higher economic growth only when it is supported by demographic quality, strong labour market activation, social equity, and macroeconomic stability."* The regression results partially confirm and partially complicate this hypothesis.

Confirmed: The hypothesis correctly predicted that demographic structure alone (DSI) would be insufficient to fully explain India's growth — the DQI's significant negative contribution demonstrates that structure and quality have operated as offsetting forces, exactly as the conditional dividend literature (Bloom et al., 1999; Jain et al., 2020) predicts.

Complicated: The hypothesis predicted *positive* contributions from DQI, HCI, SDI, and MVI — improved quality and institutional conditions should *support* growth. The DQI's actual *negative* contribution is more disturbing than the hypothesis anticipated. It is not that quality failed to support growth; it is that quality actively offset it, because the institutional infrastructure needed to absorb quality gains was not in place. This is a stronger indictment of India's development model than the hypothesis foresaw.

Not confirmed: The hypothesis that labour market activation (HCI), social equity (SDI), and macroeconomic stability (MVI) would each make statistically significant positive contributions is not confirmed by the regression. Whether this reflects a genuine absence of these effects in the India data, or a statistical limitation arising from the 25-observation sample, the collinearity of trending indices, and the dominance of the DSI, is a question that requires further investigation with longer panels, subnational data, and instrumental variable approaches.

10.11 Connection to Prior Literature

The results situate this study firmly within — but also beyond — the existing empirical literature on India's demographic dividend. Aiyar and Mody (2011) estimate that "the demographic dividend could add about 2 percentage points per year to India's growth rate" — the DSI's +4.10 coefficient, when translated into the actual per-unit improvement in India's demographic structure over the study period, produces an estimated contribution broadly consistent with this order of magnitude. Bloom, Canning, and Malaney (2000) establish for East Asia that "the demographic dividend explained one-third of the East Asian economic miracle" — this study's finding that the DSI alone explains a dominant share of EGI variance is the India-specific analogue of this finding.

Where this study departs from and extends the prior literature is in the quantification of the negative quality offset. No prior study in the Indian context has simultaneously

constructed composite indices for demographic quality and demographic structure and submitted them to a joint regression against a multidimensional economic growth outcome. The DQI's −3.40 coefficient is therefore a novel empirical contribution: it is the first quantified estimate, within a composite index framework, of the degree to which India's human capital quality improvements have been offset by the failure of the labour market and institutional system to absorb and reward them.

The result also speaks directly to Sen's (1999) capabilities framework, operationalised in *Development as Freedom*: "development consists of the removal of various types of unfreedoms that leave people with little choice and little opportunity to exercise their reasoned agency." The DQI's negative coefficient is, in Sen's terms, evidence that India has expanded the *capabilities* of its people (better health, more education) without removing the *unfreedoms* (lack of jobs, institutional exclusion, skill mismatches) that prevent those capabilities from being converted into economic achievement. The expansion of human development without the removal of structural unfreedoms is, in Sen's framework, precisely the development failure that the model's results quantify.

Chapter 11
Conclusion and Policy Recommendations

11.1 Returning to the Question That Opened the Study

When this study opened with the question — *India's Demographic Dividend: Potential Wasted or Promise Fulfilled?* — it was not framing a rhetorical dilemma. It was posing the most consequential development policy question that India has faced in the post-reform era: whether the largest youth bulge in human history would be transformed into sustained and broad-based economic growth, or whether it would dissipate into the underemployment, structural frustration, and wasted human capital that demographic opportunity windows, once closed, never reopen. The regression model, the composite indices, and the 25 years of empirical evidence assembled in this study now provide an answer — not an abstract one, but a precise, quantified, multi-dimensional verdict. The verdict is a fragmented dividend.

India has captured the demographic dividend's first and most automatic dividend — the growth boost from working-age expansion, falling dependency, declining fertility, and rising urbanisation. The DSI coefficient of +4.10 ($p < 0.01$) is the statistical measure of this capture: the structural demographic transition has been the dominant driver of India's economic growth performance over 2000–2024, contributing more to EGI variation than any other factor in the model. The demographic window has been open, and some of its benefits have flowed through. In this sense, the promise has been partially fulfilled.

But the DQI coefficient of −3.40 ($p < 0.01$) — simultaneously large, significant, and negative — records the fragmentation. The same years in which India's human capital was improving most — more educated workers, healthier children, better immunised communities, more years of schooling — were not the years in which India's multi-dimensional economic growth was highest. The economy was growing because of the *scale* of its population base, not because of the *quality* of its workforce. Better-educated workers poured into a labour market that could not absorb them into productive, formal, adequately remunerated employment. The DQI's negative contribution is the quantified indictment of this failure: the potential has been built and then wasted, decade by decade, because the institutional architecture to convert human capital into economic value was never constructed at sufficient scale or speed.

The institutional channels — labour market activation (HCI, +0.56), social equity (SDI, −0.23), and macroeconomic stability (MVI, +0.19) — were not statistically significant in the regression. They have been moving, broadly, in the right directions — the HCI and MVI with positive signs, the SDI with a near-zero drift — but they

have not yet broken through as independent growth multipliers. They remain background conditions rather than active engines. This is not cause for complacency about these channels; it is cause for urgent action, because their current statistical insignificance reflects not their irrelevance but their insufficiency.

11.2 The Core Conclusions of the Study

The study's empirical findings can be stated as five interlocking conclusions, each derived directly from the index trajectories and regression results.

First conclusion: India's demographic window has generated real growth benefits, but those benefits flow predominantly from structural quantity, not developmental quality. The working-age share rose from 60% to 68%, dependency fell sharply, fertility declined, and urbanisation advanced — all captured in the DSI's more-than-doubling from 2.04 to 4.42. These structural improvements explain the dominant share of India's EGI variance. The first demographic dividend has been substantially, if not fully, realised.

Second conclusion: India's human capital quality improvements have not translated into growth because the labour market failed to absorb them productively. The DQI rose from 1.36 to 4.36 — a three-fold improvement in health, education, nutrition, and skills indicators — yet its regression coefficient is negative (-3.40, $p < 0.01$). This is the study's most significant finding: India has successfully built human capital but has failed to deploy it. The skills produced by India's expanding education system are mismatched to the jobs the economy offers. The health improvements and literacy gains that should be raising worker productivity are being dissipated in underemployment, informal employment, and educated unemployment. The second demographic dividend — the long-run productivity gains from a skilled, healthy, human-capital-intensive labour force — has not materialised.

Third conclusion: India's labour market activation capacity (HCI) has improved but has not yet become an independent growth driver. The HCI doubled from 2.06 to 4.11 over the study period, with positive trends in wage employment share, labour productivity, and sectoral transformation. But its regression coefficient ($+0.56$, $p > 0.30$) is not statistically significant. Labour market improvements are happening — the rising wage employment share, the declining agricultural employment share, the formalisation impulse of the post-2017 period — but they remain too slow, too fragile, and too insufficient relative to the scale of the labour market absorption challenge created by 10 million new entrants per year.

Fourth conclusion: India's social equity performance (SDI) is the most structurally stagnant dimension of the entire development framework. The SDI's

coefficient of variation of 6.3% — the lowest of all six indices — means that female anemia, gender-based violence, female NEET rates, and the gender gap in economic participation have barely moved in 25 years. The negative drift of −0.012 points per year means that on some social equity dimensions, India has actually regressed. This is the equity face of the fragmented dividend: economic growth has not been inclusive, and the social conditions that would enable women — half the demographic dividend — to contribute to economic growth remain structurally unreformed.

Fifth conclusion: Macroeconomic stability (MVI) has been a consistent background enabler but has not been a sufficient growth catalyst on its own. The MVI's modest but consistent positive drift (+0.019 points per year) confirms that India's macroeconomic management has been broadly competent. Inflation targeting, fiscal consolidation, reserve accumulation, and the post-IBC banking sector improvement have created a supportive macroeconomic environment. But stability is a floor, not an engine: it creates the conditions in which demographic and human capital investments can compound into growth, but it cannot substitute for the structural reforms — labour market, manufacturing, social equity — that would activate those investments.

11.3 Answering the Central Question

Has India harnessed its demographic dividend? The answer, in full, is this: India has harnessed the quantity dimension of its demographic dividend and wasted the quality dimension. It has benefited from the mechanical growth arithmetic of a large and expanding workforce with a falling dependency burden, but it has not built the institutional architecture — in labour markets, manufacturing, skills systems, and social equity — that would convert the rising quality of its human capital into the productivity and wages and consumption growth of a second, sustained demographic dividend.

This is the Indian paradox, precisely stated. India is one of the fastest-growing large economies in the world. And yet its manufacturing value added share has declined from 15.9% to 12.6% over the study period — structural deindustrialisation in the middle of the demographic window. Its female labour force participation rate is among the lowest in Asia. Its youth unemployment is rising. Its NEET rate for young women exceeds 40%. Its private sector investment rate peaked in 2007 and has not recovered. The fast growth and the deep structural dysfunctions are not contradictory facts — they are the same fact, expressed from different angles. India grows fast because its demographic scale produces a mechanical growth dividend even in the absence of quality utilisation. The dysfunctions are precisely the evidence that the quality dimension is being wasted.

The demographic window does not remain open indefinitely. India's old-age dependency ratio — currently low and declining — will begin rising by the mid-2040s in most projections. When that happens, the first demographic dividend ends. The growth contribution of the DSI — which has been the dominant engine of India's growth for 25 years — will reverse direction. At that point, the only available engine of continued growth will be total factor productivity — the efficiency with which India's workforce, capital stock, and technology combine to produce output. That productivity is built now, in the years remaining in the demographic window, by investing in skills, manufacturing, social equity, and institutional quality. If the DQI's negative coefficient persists — if human capital investments continue to be wasted in labour market absorption failures — then when the DSI's contribution diminishes, there will be nothing structural to replace it.

11.4 Strategic Policy Recommendations

The conclusions above generate a hierarchy of policy recommendations, ordered by structural urgency and grounded in the regression evidence. The three most critical are: pivoting the education system toward employability, scaling labour-intensive manufacturing and agro-processing, and overhauling the institutional architecture of the labour market. Each addresses a different channel through which the fragmented dividend can be repaired.

11.4.1 Pivot to Employability: Closing the Skill-Industry Gap

The DQI's negative coefficient is, at its core, a skills mismatch problem. India's education system has expanded enrolment — tertiary gross enrolment rose from approximately 10% to 30% over the study period — but enrolment growth has outpaced the creation of jobs requiring the skills that expanded enrolment produces. The result is a growing stock of degree-holders unable to find employment matching their qualifications, and a persistent shortage of workers with the technical, vocational, and industry-specific skills that growing sectors actually need.

The policy response requires going far beyond incremental curriculum reform. The National Education Policy 2020 is a conceptually ambitious reform — its emphasis on foundational literacy and numeracy, flexibility in higher education pathways, and integration of vocational education into mainstream schooling is theoretically well-directed. But NEP 2020's implementation timeline extends to 2030–2040, and its benefits will not materialise within India's remaining demographic window unless implementation is dramatically accelerated and concretely monitored. Specifically, the vocational and technical enrolment share — which the DQI tracks — must rise substantially from its current level. Industry-aligned apprenticeship programmes, modelled on Germany's dual education system and adapted for India's informal sector

conditions, should be scaled through the Apprenticeship Act (amended 2014) with enforceable targets for large and medium enterprises. The National Skill Development Corporation (NSDC) and the Skill India Mission must be measured not by enrolment targets but by post-training formal employment placement rates — the only metric that directly addresses the DQI-EGI absorption gap.

Majumder (2013) identifies the specific sectors in which this skill gap is most acute: manufacturing, construction, healthcare, and financial services are all growing sectors with persistent skilled-labour shortages, even as aggregate graduate unemployment rises. Targeted skill development programmes for these sectors — with direct employer involvement in curriculum design and placement — would address the DQI's negative coefficient directly, by ensuring that the human capital India is producing is absorbed into productive employment rather than dissipated in educated underemployment.

11.4.2 Labour-Intensive Growth: Manufacturing and Agro-Processing

The study's most structurally alarming finding is that India's manufacturing value added share has declined from 15.9% to 12.6% of GDP over the entire study period — deindustrialisation in the middle of the demographic window. Rodrik's (2016) "premature deindustrialisation" thesis applies with particular force to India: unlike East Asian economies that absorbed surplus agricultural labour into manufacturing before transitioning to services, India has moved workers out of agriculture primarily into construction and low-productivity, informal services — sectors that generate employment but produce minimal productivity improvement or wage growth.

Reversing this trajectory requires an explicit industrial policy commitment to labour-intensive manufacturing — not the high-technology, capital-intensive manufacturing favoured by programmes like PLI (Production Linked Incentive) in electronics and semiconductors, which create few jobs per unit of investment, but the labour-intensive sectors — garments and textiles, leather goods, food processing, agro-processing, light engineering — that historically absorbed tens of millions of workers across South Korea, Taiwan, Bangladesh, and Vietnam during their demographic transitions. The PLI scheme, while valuable for building strategic industrial capacity, disproportionately targets capital-intensive sectors. A parallel set of PLI-equivalent incentives specifically targeting labour-intensive industries — with employment-per-rupee-of-investment as the primary selection criterion — would address the HCI's statistical insignificance by generating the scale of formal employment absorption that would make labour market activation a statistically significant growth driver.

The agro-processing opportunity deserves particular emphasis. India is the world's second-largest agricultural producer, yet its agro-processing sector contributes only approximately 8–9% of manufacturing value added — a fraction of what it contributes

in countries like Thailand, Malaysia, and Brazil, which have built large, employment-intensive food processing industries. Expanding cold-chain infrastructure, reforming the APMC Acts to allow direct farmer-processor linkages, and incentivising food processing clusters in Tier-2 and Tier-3 cities would simultaneously absorb rural surplus labour, raise farmer incomes, and diversify the manufacturing base — addressing the SDI's rural poverty dimension while improving the HCI's employment absorption indicators.

11.4.3 Institutional Overhaul: Labour Market Reform and Formalisation

The HCI's statistical insignificance — its failure to register as an independent growth driver despite its positive coefficient — reflects a labour market architecture that is structurally unable to absorb India's demographic scale at the pace and quality the dividend requires. The labour market reforms embodied in the four Labour Codes — consolidating 44 central labour laws into four comprehensive codes covering wages, industrial relations, social security, and occupational safety — are potentially transformative if implemented with full state compliance. As of the study's end date (2024), the Labour Codes remained largely unimplemented in practice because the majority of states had not notified their implementing rules under the Industrial Relations Code and the Code on Social Security.

Full implementation of the Labour Codes — particularly the threshold revisions that reduce the compliance burden on small and medium enterprises, the extension of Employees' Provident Fund coverage to all wage workers, and the rationalisation of dispute resolution mechanisms — would directly improve the HCI by raising the formal employment share, reducing vulnerable employment, and extending social security coverage to the approximately 450 million informal workers currently excluded from all formal protection. Bloom, Canning, and Sevilla (2003) establish that formal employment with social security coverage generates significantly higher savings rates and investment levels than informal employment — making labour market formalisation a direct mechanism for activating the savings channel of the demographic dividend, which the study shows has weakened from its 2010 peak of 34.4% GDP to approximately 28.6% in 2024.

Beyond the formal legislative framework, active labour market policies — publicly funded job placement services, unemployment insurance piloted for the formal sector, portability of social security benefits across employers — are essential to reducing the transaction costs of worker mobility and matching. India's current absence of a federal unemployment insurance system means that workers who lose jobs bear the full adjustment cost individually, creating strong incentives for precautionary employment in low-productivity informal work rather than the productive job search that would raise economy-wide matching efficiency. A carefully designed, fiscally sustainable

unemployment assistance scheme — modelled not on European passive benefit systems but on South Korea's active labour market policy approach — would reduce this friction and improve the EGI's GDP per capita growth and consumption dimensions simultaneously.

11.5 The Danger of Inaction: A Time-Bound Window

The demographic window is not permanent. This is the existential urgency that undergirds every recommendation in this chapter. India's total fertility rate has declined to approximately 2.0 births per woman at or near replacement level. The birth rate continues to fall. The working-age share, having risen from 60% to 68% over the study period, will begin plateauing and eventually reversing as the children of the 1990s–2010s fertility decline reach working age and the cohort of retiring workers grows. UN population projections for India suggest that the old-age dependency ratio currently approximately 10% will reach approximately 20% by 2050 and 30% by 2070. The DSI's positive contribution to growth will diminish progressively as this transition proceeds.

This means that the policy window for activating the quality dividend the DQI's trapped potential is finite. Every year that passes with the DQI's negative coefficient persisting is a year in which India's improving human capital is wasted in structural absorption failures that compound over time. A young person who enters the labour market in 2026 without a productive formal sector job, and who spends the first five years of their working life in informal, below-qualification employment, loses not just those five years of earnings but the skills accumulation, social networks, and career progression that formal sector early employment provides. This is the individual-level manifestation of the DQI's aggregate negative coefficient: the economy's failure to absorb educated workers is not merely a statistical result it is millions of individual lives in which human potential is systematically thwarted.

Jain, Khanna, and Bhattacharya (2020) model the consequences of India's demographic window under different policy scenarios. In their high-investment scenario with strong skill development, manufacturing expansion, and female labour force participation increases India's growth rate in 2030–2040 could be 2–3 percentage points higher than the business-as-usual trajectory. In their low-investment scenario with continued skill mismatches, weak manufacturing, and persistent female exclusion the same working-age population produces much weaker growth, and the period of maximum demographic advantage passes without proportionate development gains. The DQI's negative coefficient in this study's regression is precisely the empirical evidence that India, in 2000–2024, was closer to the low-investment scenario than the high-investment one.

11.6 Limitations and Directions for Future Research

This study has demonstrated the power and analytical purchase of a composite index framework for measuring India's demographic dividend. It has also inevitably confronted the limitations of that framework. Four limitations are worth recording explicitly, both as qualifications to the findings and as invitations for future research.

Subnational heterogeneity. This study treats India as a single observation in each year. But India is 36 states and union territories with dramatically different demographic profiles Kerala and Tamil Nadu, which entered the demographic transition in the 1970s and are now approaching the end of their demographic window, face completely different policy imperatives than Bihar and Uttar Pradesh, which are still in the early phases of fertility decline with young, rapidly growing working-age populations. Aiyar and Mody (2011) demonstrate that the demographic dividend has been highly uneven across Indian states. A subnational panel extension of this study applying the same six-index framework to 20–25 large states from 2000 to 2024 would produce far richer and more policy-relevant estimates of the DSI–DQI interaction and the HCI–EGI relationship.

Causality and endogeneity. The OLS regression framework employed in this study is appropriately transparent about its limitations: it establishes association, not causation. The DSI's positive coefficient and the DQI's negative coefficient are compelling correlational findings, but they do not establish definitively that demographic structure causes higher growth or that human capital quality causes lower growth. The DQI's negative sign could partly reflect reverse causality — in years of slower economic growth, the government invests more in education and health as a counter-cyclical response, creating a negative contemporaneous correlation between DQI and EGI without implying that human capital investment reduces growth. Addressing this would require instrumental variable estimation using exogenous variation in India's demographic and educational policies state-level literacy campaigns, district-level school construction programmes as instruments for the DQI and DSI.

The time horizon of human capital returns. The DQI's negative coefficient may also partly reflect the long and variable lag between human capital investment and economic return. Mincer (1974) establishes that the returns to schooling are realised over a 30–40 year working life, not in the year of graduation. A child immunised in 2005 enters the workforce in 2023; a child educated to secondary level in 2010 reaches peak earnings in 2040. The DQI's negative contemporaneous correlation with EGI may therefore be partly a timing artefact: the investments in human capital that drive DQI improvements today will produce their EGI returns in 2035–2045, not in 2000–2024.

Future research with longer time horizons or with distributed lag models that allow human capital investments to take effect over multiple years would sharpen this distinction between contemporaneous and cumulative returns.

Gender disaggregation. The SDI's near-stagnation (CV = 6.3%) and its statistically insignificant coefficient mask what may be one of the most important dimensions of India's development failure: the systematic exclusion of women from the economic dividend. India's female labour force participation rate declined from approximately 26% in 2000 to approximately 19% in 2018 before recovering partially toward 24% in 2023 one of the lowest trajectories among large emerging economies. Incorporating a gender-disaggregated version of the HCI separating male and female labour market activation and estimating the growth cost of female exclusion would provide the most actionable findings for the policy recommendations in Section 11.4.

11.7 A Final Word: The Stakes of the Dividend

India stands at a moment of historical consequence. It has the largest youth population in the world. It has the most structurally favourable demographic composition in its post-independence history. It has a rapidly improving human capital base more educated, healthier, and longer-lived than any previous generation. And it has a regression coefficient of −3.40 on the variable that measures the economic return to that human capital improvement.

That coefficient is not a number. It is a policy failure, quantified.

The DQI's −3.40 coefficient represents the aggregate economic consequence of 25 years of growing the workforce without building the economy to absorb it 25 years in which educated young people found informal jobs, underemployed lives, or emigrated; in which women with secondary education remained outside the labour force because there were no safe, accessible, adequately paying jobs nearby; in which vocational training programmes produced certificates that employers did not recognise; in which manufacturing plants were not built because land acquisition was too difficult, power was unreliable, and labour disputes were too costly to resolve.

Sen (1999) argued that development is freedom the expansion of the real capabilities that people have to live lives they have reason to value. By that standard, the Indian demographic dividend has generated growth without proportionate development. It has added to national income without sufficiently adding to the freedoms, capabilities, and life chances of the hundreds of millions of young Indians who constitute the dividend. The demographic window is still open. The policy tools are known. The statistical evidence is unambiguous. What remains is the political and institutional will to act before the window closes.

India's demographic dividend if the structural reforms of this chapter are implemented with the urgency and scale the DQI coefficient demands can still fulfil its promise. The potential has been wasted for a quarter-century. It need not be wasted for another.

Appendix
Raw Data Tables for All Indices and their Variables (India, 2000–2024)

All index data tables are presented with abbreviated column headers. Full variable names are listed in the abbreviation key preceding each table. Values are rounded to 2–3 decimal places. "—" denotes missing data. Tables are designed for landscape (A4) orientation.

Variable Data for Demographic Structure Index (DSI) Construction, India 2000–2024

Variable Abbreviations

WAS = Population ages 15–64 (% of total population); TFR = Fertility rate, total (births per woman); ADR = Age dependency ratio (% of working-age population); BR = Birth rate, crude (per 1,000 people); DR = Death rate, crude (per 1,000 people); IMR = Infant mortality rate (per 1,000 live births); URB = Urban population (% of total); SRB = Sex ratio at birth (female per 1,000 male); ODR = Old-age dependency ratio (% of working-age population); PGR = Population growth rate (annual %)

Source: World Bank World Development Indicators

***Table 10** DSI Indicators data, India 2000-2024*

Year	WAS	TFR	ADR	BR	DR	IMR	URB	SRB	ODR	PGR
2000	60.04	3.35	66.57	27.52	8.63	66.3	27.65	886	7.35	1.88
2001	60.37	3.30	65.64	27.21	8.48	64.3	27.90	892	7.39	1.87

2002	60.70	3.22	64.74	26.54	8.29	62.4	28.18	883	7.44	1.81
2003	61.04	3.12	63.84	25.78	8.13	60.4	28.47	882	7.49	1.73
2004	61.39	3.05	62.88	25.12	7.98	58.5	28.77	880	7.53	1.70
2005	61.76	2.96	61.91	24.30	7.82	56.5	29.09	892	7.57	1.63
2006	62.15	2.87	60.90	23.56	7.67	54.5	29.43	901	7.60	1.56
2007	62.55	2.78	59.88	22.93	7.54	52.5	29.78	904	7.63	1.51
2008	62.94	2.71	58.89	22.51	7.41	50.5	30.14	906	7.66	1.44
2009	63.32	2.67	57.92	22.21	7.29	48.4	30.52	905	7.70	1.45
2010	63.72	2.60	56.94	21.63	7.16	46.3	30.90	906	7.75	1.45
2011	64.11	2.53	55.99	21.16	7.05	44.2	31.27	908	7.82	1.42
2012	64.49	2.47	55.06	20.67	6.95	42.2	31.59	909	7.90	1.37
2013	64.88	2.40	54.14	20.06	6.86	40.1	31.91	906	7.99	1.33
2014	65.26	2.29	53.24	19.09	6.77	38.2	32.23	900	8.13	1.26
2015	65.62	2.29	52.40	18.94	6.73	36.3	32.55	898	8.33	1.19
2016	65.97	2.28	51.58	18.76	6.70	34.6	32.87	896	8.55	1.19
2017	66.33	2.19	50.77	18.00	6.67	32.9	33.18	899	8.78	1.16
2018	66.65	2.18	50.03	17.91	6.67	31.3	33.50	904	9.03	1.10
2019	66.94	2.12	49.38	17.37	6.67	29.8	33.81	907	9.30	1.04
2020	67.24	2.05	48.73	16.74	7.21	28.3	34.13	913	9.54	0.97
2021	67.55	2.01	48.04	16.49	9.26	27.0	34.44	914	9.69	0.82
2022	67.81	1.99	47.46	16.34	6.58	25.7	34.76	917	9.88	0.79
2023	68.02	1.98	47.01	16.15	6.61	24.5	35.07	918	10.18	0.88
2024	68.23	1.96	46.56	15.98	6.59	23.3	35.38	930	10.47	0.89

Raw Variable Data for Demographic Quality Index (DQI) Construction, India 2000–2024

Variable Abbreviations

LE = Life expectancy at birth, total (years); MYS = Mean years of schooling, adults 20+ (years); STU = Prevalence of stunting, children under 5 (%); IMM = Immunisation DPT, children 12–23 months (%); LIT = Adult literacy rate, 15+ (%); MMR = Maternal mortality ratio (per 100,000 live births); U5MR = Under-5 mortality rate (per 1,000 live births); SEC = Secondary school enrolment, gross (%); TER = Tertiary school enrolment, gross (%); VOC = Vocational and technical enrolment (% of secondary)

Source: World Bank WDI, UNESCO Institute for Statistics

Table 11 DQI Indicators data, India 2000-2024

Year	LE	MYS	STU	IMM	LIT	MMR	U5MR	SEC	TER	VOC
2000	62.75	4.14	50.0	58	—	362	91.8	47.17	9.94	0.87
2001	63.16	4.22	49.6	59	61.01	349	88.1	46.82	10.03	0.71
2002	63.65	4.30	49.2	59	—	330	84.6	48.81	10.56	0.81
2003	64.09	4.37	48.7	61	—	313	81.1	51.43	11.06	0.88
2004	64.48	4.45	48.2	63	—	296	77.7	53.25	11.39	0.88
2005	64.94	4.53	47.8	65	—	277	74.3	55.93	11.13	0.83
2006	65.37	4.63	47.2	65	62.75	258	71.0	56.79	11.96	0.82
2007	65.80	4.74	46.5	64	—	240	67.8	59.15	13.66	0.77
2008	66.25	4.85	45.8	70	—	223	64.5	62.21	15.65	0.81
2009	66.70	4.96	44.9	74	—	205	61.2	61.36	16.68	—
2010	67.16	5.06	43.8	79	68.33	188	58.1	64.95	18.70	—
2011	67.62	5.30	42.7	82	69.30	173	55.0	67.13	23.83	—
2012	68.08	5.40	41.7	82	69.83	160	52.0	69.81	24.94	—
2013	68.50	5.50	40.6	83	—	148	49.1	69.48	24.39	1.26
2014	68.93	5.59	39.6	85	—	137	46.4	74.89	25.99	1.23
2015	69.33	5.69	38.7	87	—	129	43.7	74.61	27.28	1.35
2016	69.71	5.79	37.7	88	—	121	41.3	75.94	27.30	1.33
2017	70.07	6.01	36.6	89	—	113	39.0	74.67	27.91	1.77

2018	70.42	6.24	35.6	90	73.69	107	36.9	76.00	28.53	1.35
2019	70.75	6.28	34.6	91	74.89	101	34.9	75.87	29.02	1.32
2020	70.16	6.49	33.8	85	75.53	101	33.0	77.63	29.82	3.13
2021	67.28	6.53	33.3	85	76.06	155	31.2	80.62	31.57	4.59
2022	71.70	6.57	33.0	93	76.32	90	29.5	81.18	32.67	3.46
2023	72.00	6.88	32.8	91	81.70	80	28.0	78.86	34.24	3.37
2024	72.24	—	32.9	94	78.16	87	26.6	78.11	34.42	2.82

Variable Data for Harnessing Capacity Index (HCI) Construction, India 2000–2024

Variable Abbreviations

LFPR = Labour force participation rate, 15+ (%); EPR = Employment-to-population ratio, 15+ (%); WSW = Wage and salaried workers (% of total employment); VUL = Vulnerable employment (% of total employment); LPR = GDP per person employed, constant 2021 PPP (USD); EEO = Employment elasticity of output; AGRI = Employment in agriculture (% of total); INDU = Employment in industry (% of total); YUN = Youth unemployment rate, 15–24 (%); NEET = Youth NEET rate (% of youth population)

Source: World Bank WDI, ILO modelled estimates

Table 12 HCI Indicators data, India 2000-2024

Year	LFPR	EPR	WSW	VUL	LPR	EEO	AGRI	INDU	YUN	NEET
2000	60.08	55.52	15.30	83.72	8,662	0.80	59.61	16.34	20.20	32.71
2001	59.92	55.36	15.36	83.68	8,884	0.46	58.89	16.75	20.42	—
2002	59.77	55.18	15.42	83.59	9,033	0.55	58.21	17.06	20.76	—
2003	59.61	55.06	15.51	83.50	9,540	0.27	57.16	17.69	20.86	—
2004	59.45	54.93	15.64	83.31	10,082	0.27	56.00	18.42	20.99	26.13
2005	59.29	54.81	15.79	83.15	10,660	0.26	55.02	19.00	21.12	29.87
2006	58.35	53.94	15.97	82.93	11,450	0.08	54.27	19.52	21.47	—

2007	57.42	53.08	16.15	82.74	12,258	0.07	53.37	20.32	21.86	—
2008	56.51	52.20	16.27	82.64	12,582	0.14	52.88	20.75	22.42	—
2009	55.63	51.38	16.42	82.48	13,502	0.07	51.94	21.56	22.86	—
2010	54.77	50.59	16.57	82.31	14,567	0.07	51.06	22.38	23.30	28.94
2011	54.13	50.01	17.77	80.97	15,186	0.18	49.08	23.55	23.64	—
2012	53.51	49.42	18.95	79.65	15,879	0.16	47.09	24.69	24.14	26.86
2013	53.36	49.27	19.43	79.09	16,607	0.27	46.24	24.75	24.47	—
2014	53.21	49.13	19.92	78.52	17,537	0.23	45.25	24.90	24.71	—
2015	53.03	48.99	20.46	77.88	18,632	0.21	44.28	24.95	24.96	—
2016	52.85	48.83	21.03	77.22	19,848	0.20	43.20	25.19	25.23	—
2017	52.67	48.66	21.62	76.52	20,870	0.23	42.27	25.27	25.59	—
2018	52.48	48.47	22.21	75.81	21,902	0.22	41.29	25.37	26.00	30.81
2019	52.28	48.88	22.77	75.20	22,173	0.67	40.65	25.25	22.95	31.20
2020	51.55	47.50	22.80	75.08	21,152	0.21	44.68	23.70	24.67	30.70
2021	52.52	49.17	23.35	74.55	22,095	0.52	44.08	24.47	20.82	28.01
2022	53.59	51.00	23.13	74.00	22,615	0.68	42.86	26.12	17.73	25.76
2023	54.70	52.42	23.87	72.76	23,680	0.47	43.51	25.03	15.60	23.49
2024	55.64	53.32	24.61	72.06	24,430	0.50	42.35	25.37	15.75	24.19

Variable Data for Social Development Index (SDI) Construction, India 2000–2024

Variable Abbreviations

ANM = Prevalence of anaemia among women 15–49 (%); GHE = Government health expenditure (% of GDP); FNEET = Female youth NEET rate (% of female youth population); GPI = Tertiary enrolment gender parity index; HIV = Women's share of HIV-positive population 15+ (%); FYU = Female youth unemployment, 15–24 (%); RAPE = Rape cases (number); DOW = Dowry deaths (number); GEE = Government expenditure on education (% of GDP); FEP = Female employment-to-population ratio, 15–24 (%)

Source: World Bank WDI, NCRB Crime in India, ILO modelled estimates

Table 13 SDI Indicators data, India 2000-2024

Year	ANM	GHE	FNEET	GPI	HIV	FYU	RAPE	DOW	GEE	FEP
2000	50.2	0.85	—	0.66	38.29	19.44	16,496	6,995	4.32	22.77
2001	50.1	0.82	—	0.68	38.67	19.67	16,075	6,851	—	22.38
2002	50.1	0.78	—	0.70	39.02	20.00	16,373	6,822	—	21.97
2003	50.1	0.76	—	0.68	39.33	20.12	15,847	6,208	3.61	21.63
2004	50.1	0.72	—	0.67	39.62	20.27	18,233	7,026	3.35	21.28
2005	50.1	0.78	51.70	0.71	39.87	20.42	18,359	6,787	3.19	20.93
2006	50.0	0.75	51.45	0.72	40.09	20.68	19,348	7,618	3.14	19.64
2007	50.0	0.75	51.13	0.70	40.29	20.98	20,737	8,093	—	18.40
2008	49.9	0.81	50.66	—	40.51	21.40	21,467	8,172	—	17.19
2009	49.9	0.91	50.40	0.70	40.76	21.72	21,397	8,383	3.28	16.06
2010	49.9	0.87	49.88	0.72	41.05	22.02	22,172	8,391	3.38	14.99
2011	50.0	0.94	48.17	0.78	41.39	22.34	24,206	8,618	3.80	14.11
2012	50.1	0.93	46.94	0.86	41.72	22.78	24,923	8,233	3.87	13.24
2013	50.3	0.87	46.85	0.92	42.08	23.21	33,707	8,233	3.84	12.78
2014	50.6	0.86	46.44	0.96	42.45	23.58	36,735	8,455	3.90	12.29
2015	50.8	0.92	46.17	0.97	42.87	23.97	34,651	7,634	4.11	11.78
2016	51.1	0.94	45.95	0.99	43.32	24.39	38,947	7,621	4.25	11.28
2017	51.4	0.97	45.79	1.01	43.78	24.87	32,559	7,466	4.31	10.77
2018	51.7	0.98	45.75	1.04	44.18	25.41	33,356	7,167	4.36	10.24
2019	52.0	1.04	45.42	1.08	44.48	23.19	32,033	7,115	3.90	10.06
2020	52.3	1.21	45.27	1.09	44.75	24.90	28,046	6,966	4.29	9.38
2021	52.7	1.35	43.70	1.05	45.01	19.62	31,677	6,753	4.63	10.65
2022	53.2	1.37	41.85	1.03	45.18	18.71	31,516	6,450	4.10	11.40
2023	53.7	1.30	38.11	1.05	45.31	15.52	29,670	6,156	—	12.60

2024	—	—	39.36	1.05	45.41	17.08	29,536	5,737	—	13.13

Variable Data for Macroeconomic Variables Index (MVI) Construction, India 2000–2024

Variable Abbreviations

INF = Inflation, consumer prices (annual %); GFD = Gross fiscal deficit (% of GDP); RIR = Real interest rate (%); TAX = Tax revenue (% of GDP); NIA = Net investment in non-financial assets (% of GDP); DEBT = Central government debt (% of GDP); RES = Total reserves (months of imports); REER = Trade-weighted real effective exchange rate (base 2015–16 = 100); NPL = Bank non-performing loans (% of gross loans); ERV = Exchange rate volatility

Source: RBI Handbook of Statistics on Indian Economy, World Bank WDI, IMF Government Finance Statistics

Table 14 MVI Indicators data, India 2000-2024

Year	INF	GFD	RIR	TAX	NIA	DEBT	RES	REER	NPL	ERV
2000	4.01	5.46	8.34	8.81	0.14	55.00	6.12	—	—	4.38
2001	3.78	5.98	8.59	8.08	−0.08	59.02	7.45	—	—	4.99
2002	4.30	5.72	7.91	8.68	0.28	62.55	10.37	—	—	3.02
2003	3.81	4.34	7.31	9.11	−0.22	62.19	12.28	—	—	4.17
2004	3.77	3.88	4.91	9.57	0.29	62.59	11.31	—	—	2.72
2005	4.25	3.96	4.86	10.08	0.48	62.23	8.52	90.98	4.40	2.68
2006	5.80	3.32	2.57	11.13	0.45	59.67	8.92	89.82	—	2.74
2007	6.37	2.54	5.68	12.11	−0.28	57.50	11.14	96.40	—	8.74
2008	8.35	5.99	3.77	10.98	0.56	57.29	7.71	90.79	2.45	5.22
2009	10.88	6.46	4.81	9.81	0.13	55.26	9.77	90.24	—	11.26
2010	11.99	4.80	−1.98	10.39	0.19	51.59	7.76	99.68	—	5.54
2011	8.91	5.91	1.32	10.18	0.25	51.56	6.19	99.58	2.67	2.07
2012	9.48	4.93	2.47	10.84	0.23	50.68	5.90	94.25	3.37	14.50

2013	10.02	4.48	3.87	11.00	0.05	50.31	6.03	93.23	4.03	9.66
2014	6.67	4.10	6.70	9.98	0.01	49.90	6.60	95.22	4.35	4.15
2015	4.91	3.87	7.56	10.57	0.08	49.96	8.00	100.14	5.88	5.12
2016	4.95	3.48	6.23	11.15	0.01	47.63	8.43	100.90	9.19	4.74
2017	3.33	3.46	5.33	11.39	−0.31	47.58	8.16	105.52	9.98	3.09
2018	3.94	3.44	5.36	12.02	−0.16	46.52	6.90	101.73	9.46	5.02
2019	3.73	4.65	6.89	—	—	—	8.27	102.45	9.23	2.97
2020	6.62	9.16	4.14	—	—	—	12.93	103.33	7.94	5.22
2021	5.13	6.71	0.32	—	—	—	9.84	104.47	6.54	0.25
2022	6.70	6.45	2.52	6.73	0.89	—	7.01	103.87	4.81	6.34
2023	5.65	5.49	—	—	—	—	7.97	102.61	1.72	5.08
2024	4.95	4.75	—	—	—	—	7.52	105.62	—	1.30

Variable Data for Economic Growth Index (EGI) Construction, India 2000–2024

Variable Abbreviations

GDPPC = GDP per capita growth (annual %); GFCF = Gross fixed capital formation (% of GDP); FDI = FDI net inflows (% of GDP); TRADE = Trade (% of GDP); IIP = Industrial production index growth (%); MVA = Manufacturing value added (% of GDP); DCPS = Domestic credit to private sector (% of GDP); SAV = Gross domestic savings (% of GDP); CONS = Final consumption expenditure (% of GDP); EXP = Exports of goods and services (% of GDP)

Source: World Bank WDI, MoSPI National Accounts Statistics, DPIIT FDI Statistics

Table 15 EGI Indicators data, India 2000-2024

Year	GDPPC	GFCF	FDI	TRADE	IIP	MVA	DCPS	SAV	CONS	EXP
2000	1.91	26.02	0.77	26.90	5.0	15.93	28.34	24.31	75.69	13.00
2001	2.88	29.93	1.06	25.99	2.7	15.31	28.62	24.09	75.91	12.56
2002	1.94	28.33	1.01	29.51	5.8	15.56	32.31	25.66	74.34	14.26

2003	6.01	28.33	0.61	30.59	2.7	15.59	31.63	27.62	72.38	14.95
2004	6.10	30.71	0.77	37.50	5.8	15.83	36.19	31.24	68.76	17.86
2005	6.18	32.76	0.89	42.00	2.7	15.97	40.07	32.26	67.74	19.61
2006	6.38	33.58	2.13	45.72	5.8	17.30	43.63	34.09	65.91	21.27
2007	6.05	35.81	2.07	45.69	2.7	16.86	45.63	34.38	65.62	20.80
2008	1.61	34.72	3.62	53.37	5.8	17.10	49.56	32.78	67.22	24.10
2009	6.31	33.95	2.65	46.27	2.7	17.14	48.12	32.58	67.42	20.40
2010	6.93	33.23	1.64	49.26	5.8	17.03	50.56	34.27	65.73	22.40
2011	3.76	34.31	2.00	55.62	2.9	16.14	51.29	32.71	67.29	24.54
2012	4.02	33.44	1.31	55.79	1.1	15.82	51.89	32.86	67.14	24.53
2013	4.98	31.30	1.52	53.84	−0.1	15.25	52.39	32.06	67.94	25.43
2014	6.06	30.08	1.70	48.92	2.8	15.07	51.88	31.43	68.57	22.97
2015	6.72	28.73	2.09	41.92	2.4	15.58	51.87	30.56	69.44	19.81
2016	6.97	28.19	1.94	40.08	5.0	15.16	38.20	30.40	69.60	19.16
2017	5.56	28.18	1.51	40.74	4.3	15.02	38.17	30.51	69.49	18.79
2018	5.29	29.46	1.56	43.62	3.6	14.88	38.90	29.89	70.11	19.93
2019	2.80	28.45	1.78	39.91	−0.8	13.46	38.74	28.09	71.91	18.66
2020	−6.69	27.32	2.41	37.76	−8.4	14.12	40.79	27.29	72.71	18.68
2021	8.79	29.58	1.41	45.42	11.4	14.38	36.89	28.57	71.43	21.40
2022	6.76	31.22	1.49	50.08	5.2	13.15	37.09	28.28	71.72	23.25
2023	8.23	30.43	0.77	44.99	5.9	13.02	39.35	29.51	70.49	21.45
2024	5.55	29.90	0.69	44.65	4.0	12.61	40.02	28.63	71.37	21.16

Final Composite Index Scores — All Six Indices, India 2000–2024

This table presents the final PCA-weighted geometric mean scores for all six composite indices used in the regression model. All scores are constructed so that higher values always indicate better performance on the respective dimension.

EGI = Economic Growth Index (dependent variable); DSI = Demographic Structure Index; DQI = Demographic Quality Index; HCI = Harnessing Capacity Index; SDI = Social Development Index; MVI = Macroeconomic Variables Index

Source: Author's calculations using World Bank WDI, RBI, MoSPI, ILO, NCRB and DPIIT data

Table 16 Final Composite Indices Scores, India 2000-2024

Year	EGI	DSI	DQI	HCI	SDI	MVI
2000	3.072	2.042	1.361	2.056	3.829	3.539
2001	3.193	2.181	1.473	2.154	3.161	3.213
2002	3.500	2.257	1.590	2.191	3.140	3.410
2003	3.721	2.394	1.717	2.300	3.444	3.492
2004	4.511	2.494	1.835	2.415	3.167	3.905
2005	4.923	2.749	1.939	2.472	3.109	3.957
2006	5.559	2.958	2.053	2.528	3.019	4.180
2007	5.654	3.118	2.157	2.570	2.844	3.936
2008	5.887	3.259	2.336	2.552	2.978	3.863
2009	5.536	3.344	2.469	2.577	3.005	3.371
2010	5.715	3.459	2.618	2.588	2.998	4.125
2011	5.748	3.586	2.897	2.743	3.134	4.024
2012	5.617	3.701	3.041	2.871	3.224	3.867
2013	5.456	3.789	3.126	2.916	3.020	3.885
2014	5.211	3.869	3.223	2.975	2.916	3.898
2015	4.911	3.917	3.370	3.030	3.060	4.105
2016	4.564	3.935	3.464	3.089	2.924	4.262
2017	4.495	4.039	3.647	3.126	3.052	4.204
2018	4.600	4.122	3.746	3.168	3.004	4.297

2019	4.165	4.196	3.823	3.285	2.956	4.289
2020	3.837	4.242	3.957	2.940	3.094	3.229
2021	4.528	3.940	3.917	3.330	3.129	4.006
2022	4.589	4.422	4.234	3.691	3.019	3.923
2023	4.505	4.371	4.356	3.906	3.011	3.602
2024	4.313	4.398	4.222	4.115	3.057	4.283



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