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A Mathematical Framework to Characterise Disparity in the Female-to-Male LFPR Ratio across States of India

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Abstract

We focus on the Ratio of Female-to-Male labour force participation rate (LFPR), a Sustainable Development Goal (SDG) indicator and a key indicator defined by Niti Aayog in the SDG India Index 2023–24 for measuring India's progress towards the goal of gender equality. We use mathematical techniques to show that this indicator should be considered separately for urban and rural areas. We develop a framework to statistically establish that the value of this indicator in urban areas is a proxy for the socio-cultural factors adversely impacting female LFPR across states of India. We categorise the states of India into three groups by applying the machine learning technique of clustering over this indicator for urban areas. We establish the validity of this clustering or grouping of states by noticing that the common gender discrimination factors, such as female literacy rate and crime rates against women, show noticeably different behaviours across the three categories of states. We conclude by demonstrating that if we normalise female-to-male LFPR in rural areas for socio-cultural factors, we can actually characterise the decrease in female LFPR with an increase in income levels, a phenomenon currently explained in the literature as higher LFPR in economic distress.

Keywords: Sustainable Development Goal (SDG), Gender Equality, Labour Force Participation Rate (LFPR), Female LFPR, Male LFPR, Clustering.

Introduction

India is one of the fastest-growing economies of the world. The government of India has set itself an ambitious goal of raising the gross domestic

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product (GDP) of India from US Dollars (USD) 3.7 trillion in the year 2023–24 to USD 30 trillion by 2047, the centenary year of the country's independence. To achieve this ambitious growth, it is widely recognised that India needs to grow inclusively. In particular, the labour force participation rate (LFPR) of females should increase from the current 35–40 per cent to around 60–70 per cent. The desired increase in Female LFPR (or FLFPR) is firmly embedded in the Sustainable Development Goal (SDG) 5, which states, "achieve gender equality and empower all women and girls." As per the SDG India Index compiled by the Niti Aayog, a key indicator for gender equality is the ratio of Female-to-Male LFPR (Niti Aayog, 2024, pp 111–112), where the value for India is 0.48 in 2023–24 against the longer-term target value of 1. A better understanding of the wide disparity in this indicator across the states of India is imperative to design effective policies for increasing FLFPR across all states and, in turn, to achieve the target value of 1 for India. In this paper, we focus on this indicator and develop a mathematical framework to characterise the disparity in the ratio of Female-to-Male LFPR across different states of India.

Background of the SDG-5 Indicator Female-to-Male LFPR Ratio

The labour force participation rate or LFPR emerged as an economic concept in the 1920s when the International Labour Office (1924) defined it as the share of working-age population that is either in employment or is actively seeking employment. The International Labour Organisation (ILO) standardised the gender-specific constituents of the ratio — Female LFPR and Male LFPR — around the mid-twentieth century. Female LFPR gained prominence with the rise of feminist economics in the 1970s and the 1980s. In the 1990s and the 2000s, international organisations like the World Bank and the United Nations Development Programme began systematically using female-to-male ratios (including in employment) in indices such as Gender Development Index (GDI) and Gender Inequality Index (GII). With the adoption of the Sustainable Development Goals in 2015, gender equality became a central objective (Goal 5) and the female-to-male LFPR ratio became a key indicator within the SDG framework. In the Indian context, this ratio is used as a part of the national indicator framework (NIF) to measure gender equality, with the reported female-to-male LFPR (15–59 years) increasing from 0.33 in 2018–19 to 0.48 in 2022–23.

The female-to-male LFPR ratio, along with the other female-to-male ratios such as female-to-male sex ratio at birth, female-to-male ratio in primary education, female-to-male ratio in tertiary education, female-to-male ratio of earned income, are designed and widely used in gender studies to measure relative gaps and not just absolute participation levels. These ratios implicitly control for unobserved macro-level factors affecting both female and male participation (e.g., business cycles, institutional settings), as these are partially differenced out in the ratio. Specifically, the female-to-male LFPR ratio is now widely adopted, both globally (by the ILO and the World Bank) and in India, as a key measure of gender inequality in labour force participation. The long-term objective of the female-to-male LFPR ratio as the SDG-5 indicator is to achieve the value of 1.0, which would imply equal labour force participation of men and women irrespective of economic and structural transformations.

The statistical justifications behind this indicator are as follows. Let $FLFPR$ and $MLFPR$ denote female and male participation rates, respectively. Then, the female-to-male LFPR ratio $R = \frac{FLFPR}{MLFPR}$ provides a scale-invariant indicator that normalises female participation by the male benchmark. This transformation mitigates biases arising from cross-country and cross-regional differences in overall labour market participation and demographic structures, thereby improving comparability across units and over time. From an econometric perspective, the ratio serves as a dimensionless dependent variable, reducing heteroskedasticity associated with level differences and allowing for more stable variance across observations. In log-linear specifications, $\ln(R) = \ln(\mathrm{F}LFPR) - \ln(\mathrm{M}LFPR)$, the measure can be interpreted as the log gender gap, facilitating elasticity-based interpretations and straightforward decomposition of effects. Importantly, the ratio aligns with standard practices in gender economics by capturing relative inequality rather than absolute levels, making it particularly suitable for panel data analysis and cross-country/cross-regional regressions. Importantly, since the ratio computation and interpretation are consistent with data frameworks developed by the ILO and the World Bank, this metric provides a robust and policy-relevant measure of gender disparity in labour force participation.

Review of Literature

The Labour Force Participation Rate (LFPR) emerged as a key economic indicator in the mid-1920s. It was originally defined by the International Labour Office (1924), while a recent definition is provided in the International Labour Organization (2013), as the percentage of the working-age population engaged in or seeking employment. Its relationship with industrialization was examined in the ILO (ICLSs, 1923–1947). Durand (1948) provided a seminal analysis linking LFPR to structural transformations such as industrialization and urbanization.

The ILO, in response to the rising female workforce participation, introduced a gender-disaggregated measure of LFPR, called Female LFPR or FLFPR, in ILO (1947). In an intriguing contribution, Boserup (1970) noted a U-shaped relationship between FLFPR and economic development. This U-shaped hypothesis, later formalised by Goldin (1995), suggested a decline in FLFPR during early development followed by a rise at higher income levels. The hypothesis was empirically supported by Mammen and Paxson (2000), while Blau and Kahn (2007) emphasised the role of education, incomes, and social factors in shaping women's decisions to enter the workforce.

Starting in the early 2010s, the literature on female workforce participation increasingly focused on two aspects. Firstly, paradoxes in developing economies such as India, and secondly, state- and regional-level variations in FLFPR in India. In particular, Klasen and Pieters (2012) showed that in India, women's labour supply is largely push-driven, particularly among less-educated groups, with limited evidence of growth-induced employment opportunities. Fernández (2013) highlighted the importance of cultural norms and intergenerational learning, while Lahoti and Swaminathan (2013) challenged the universality of the U-shaped hypothesis, emphasising sectoral composition over aggregate growth. Chaudhary and Verick (2014) noted that, among other factors, socio-cultural norms (such as safety concerns and household responsibilities) limit women's workforce participation and hence reduce Female LFPR, while India appears to be in a transition phase in the "U-curve" where economic growth initially leads to a decline in FLFPR. Naresh (2014) highlighted that the tribal women in India exhibit relatively high work participation due to economic necessity, but their employment remains concentrated in low-paid, informal, and economically vulnerable sectors.

Klasen and Pieters (2015) attributed the stagnation of urban FLFPR in India to a combination of income effects, rising education, and insufficient demand for female labour, emphasizing both supply and demand-side constraints. Lechman and Kaur (2015) provided cross-country support for the U-shaped relationship. Mathew (2015) argues that the decline in female labour force participation in Kerala is largely driven by the "discouraged worker effect," where women withdraw from the labour market due to limited suitable employment opportunities despite high educational attainment. Sorsa et al. (2015) find that low female labour force participation in India is driven by educational mismatch, income effects, social norms, safety concerns, and inadequate availability of suitable jobs for women. Saha et al (2016) show that declining female employment in Gujarat and Uttar Pradesh is driven by limited non-farm job opportunities, social norms, and structural changes in rural labour markets. Fletcher et al (2017) highlighted demand-side constraints and job mismatches in India, while Verick (2018) found only a weak U-shaped relationship globally. Chatterjee et al (2018) hypothesized that moderate increase in education reduces Female LFPR in India. Ghai (2018) cited patriarchy as a prominent cause for a declining FLFPR in India. Gupta (2021) finds that higher levels of violence and concerns about women's safety significantly reduce female labour force participation. Chatterjee and Sircar (2021) noted that social norms, safety concerns, unpaid domestic work and limited availability of suitable jobs for women contribute to low FLFPR. Chattopadhyay and Chowdhury (2022) noted that social restrictions, household responsibilities, caste mobility, and educational expansion reduce female LFPR.

Jain and Rani (2024) show that the relationship between women's education and labour force participation varies significantly across Indian states due to differences in socio-economic conditions, employment opportunities, and regional development patterns. Raval et al (2024) identify socio-cultural barriers, educational disparities, safety concerns, and limited employment opportunities as major factors constraining female labour force participation in Surat city. Deshpande and Singh (2024) noted that structural transformation, jobless growth and limited local labour demand contribute to low FLFPR, while Deshpande (2025) noted that increase in rural Female LFPR is primarily due to better measurement and "own-account work," often associated with survival-oriented informal activities. On the other side, many recent works continue to emphasize that higher female labour force participation is critical to economic success of nations (Salimov (2019), Sahu and Behera (2023), Kuldasheva and Ahmad (2025), Nawarathna (2025), Priya (2025)) while the increase in Female LFPR in India in recent years in rural areas is primarily driven by survival necessity even though the government schemes have been helpful (Ravi and Kapoor (2024).

Overall, the literature broadly testifies to the following five observations. Firstly, higher female LFPR is critical for faster economic development of India. Secondly, female LFPR is shaped by both economic factors (such as economic development, growth and income levels) as well as socio-cultural factors. Thirdly, in the context of India, socio-cultural factors (such as female safety concerns) negatively impact the growth of female LFPR in India. Fourthly, economic factors (especially lack of sufficient good-quality employment opportunities) significantly reduce female LFPR in India, and the recent increase in female LFPR in India (especially in rural areas) is necessity-driven, where poor women take up low-quality informal work in "distress." Fifthly, the conventional "U-shaped" curve in Female LFPR with respect to the income level or economic development is often weak because Female LFPR is impacted by non-economic factors in a complex manner at the country level.

In these observations, the phrase "women take-up low-quality informal work in distress" is used in the sense of Naresh (2014), Klasen and Pieters (2012) and Deshpande (2025), where it has been noted that women in poorer households (particularly in rural areas), out of necessity to meet subsistence living, enter the workforce to support their family's food and basic requirements. This increase in workforce participation is not due to availability of economic-growth driven employment opportunities.

Finally, in an interesting work, Nayak and Natarajan (2018) leveraged statistical techniques to analyse the regional variations in FLFPR in India by considering four broad geographic divisions of India, namely North, South, West and East. In particular, the authors used multilinear regression modelling technique to analyse the differences in FLFPR across top states in each geographical region. The authors further studied the effect of Per Capita Income on FLFPR through polynomial regression analysis. It highlights the importance of government schemes in targeting the fundamental cultural and social forces that shape patriarchy. Importantly, Nayak and Natrajan explored the promising research avenue of using mathematical/statistical techniques along with state-level data in India to analyse FLFPR in a manner which was not previously possible due to lack of data. In this paper, we take this philosophy one step further, where we use mathematical techniques in a more general way to deduce several important results.

Research Gap and Contribution

The existing body of literature on FLFPR in India is either qualitative only or relies on building a state-level or geographical-region-level statistical model to understand the key drivers of low FLFPR. The approach of state-level (or even geographical region level) mathematical modelling of FLFPR has the following limitations. Firstly, the disparity in FLFPR between rural and urban areas within a state is larger than the disparity across urban areas of different states or rural areas of different states, respectively. A more rigorous mathematical modelling of state-wise FLFPR should ideally treat urban and rural parts of each state distinctly. Secondly, the practice of modelling FLFPR at state or regional level is hampered by the 'curse of dimensionality. 'The 'curse of dimensionality' is a challenge related to building statistical and mathematical models where the data available to build the model is much smaller than the required data. Consequently, the statistical results obtained through the model are not fully reliable, at least in the conventional mathematical sense. Thirdly, grouping states on the basis of geographical proximity (as in North, South, East and West India) makes it hard to segregate the impact of socio-cultural factors from economic factors on FLFPR. This is because different states within a given geographical region of India may have similar socio-cultural factors but can be at very different levels of economic development. For example, the tiny state of Sikkim is in the geographical proximity of the state of Bihar but has almost 10 times higher per capita income. We attempt to mitigate the three limitations through a more rigorous mathematical framework comprising tools and ideas from statistics and classical machine learning.

India is a diverse country with different cities/districts/villages following very different economic and social growth trajectories. The current administrative groupings of India into states are insufficient for more careful analysis. As an example, economic and social factors in Gurugram (a city in the rural state of Haryana in North India) exhibit more similarity with Bangalore (an information technology hub that is thousands of kilometres away in South India) than with villages which are less than 10 kilometres away in rural Haryana. Due to this vast diversity, many insightful research contributions over the past decade either focus on very narrow homogeneous geographies, such as Mathew (2015) on Kerala and Raval et al (2024) on Surat, or trying to fit mathematical formulations to administrative groupings. It is not difficult to contemplate that the approach focusing on a narrow geographic region is not scalable to lakhs of villages and towns of India while the approach of considering regional groupings is not deep enough to provide specific state- or district-level insights. The mathematical model presented in this paper is (a) scalable to any numbers of states/districts/villages as long as the data for that state/district/village is available, and (b) any insights derived from can always be quantified to a statistical degree of confidence (For example, if Bangalore and Gurugram appear similar in data at 95% confidence level, it is good enough for policy-making even in the absence of high quality research justifying similarity of economic and social factors in the two cities). Such research is feasible in this time as a result of the high-volume of official data, such as the Periodic Labour Force Surveys (PLFS) released with regularity. Mathematical frameworks into feminist and labour economic research is likely to open avenues for faster and more insightful research outcomes through (a) more data being increasingly published by the government, (b) reusability of mathematical frameworks to different field and granularities, and (c) availability of existing mathematical research results in data science and machine learning which can now be applied to economic research.

Having said that, it is important to look at the overall research in context and therefore, we believe that mathematical framework-oriented data-driven research and the conventional economic research are likely to complement each other with each having its own advantages and limitations.

Our key contributions in this paper can be enumerated as follows. We propose a mathematical framework for characterising disparity in state-wise FLFPR where each state is considered as a combination of two virtual states, one for rural areas of the state and one for urban areas of the state, respectively. Using the ‘extra dimension’ accorded by the separate treatment of urban and rural areas of each state, we propose a two-factor model for modelling FLFPR: a factor combining all socio-cultural features, and another factor combining all economic and other features. We argue that this model mitigates the curse of dimensionality. Leveraging the two-factor model, we establish that the indicator *Female-to-Male LFPR Ratio*, promoted by the Niti Aayog for Goal 5 in the SDG India Index, is a strong proxy for the socio-cultural biases resulting in low FLFPR across many states of India. Applying the well-known machine learning technique of clustering to this indicator, we group (or cluster) the 29 states of India into three clusters (or three groups). The states included in one group are similar to each other in terms of the intensity of socio-cultural factors impacting female LFPR, but different from states included in the other two groups. Importantly, these three groups are different from the geographical grouping of states used commonly in the existing literature. We argue that for future framework-oriented research works in this direction, our proposed grouping of states might be more effective than geographical grouping. We validate the sanctity of these groupings by plotting the known socio-cultural biases against women across the three groups of states. We leverage the state-level indicator *Female-to-Male LFPR Ratio in Urban Areas* to *normalise* the *Female-to-male LFPR Ratio* in rural areas. Using the normalised values, we observe a partial U-curve between female LFPR and the per capita income in line with the global literature on the subject.

The rest of the paper is organised as follows. In the next section, we show mathematically that intra-state disparity in urban vs rural FLFPR is statistically higher than the disparity across states both within urban and within rural areas. Based on the results, we propose that instead of modelling FLFPR across 29 states, a better approach is to study FLFPR across 58 virtual states where each state (such as Maharashtra) is considered as two states (that is, Maharashtra-Urban and Maharashtra-Rural). In the following section, we study the cross-correlations between the four state-level data sets of $\mathrm{FLFPR}_{\mathrm{Urban}}$, $\mathrm{FLFPR}_{\mathrm{Rural}}$, $\mathrm{MLFPR}_{\mathrm{Urban}}$ and $\mathrm{MLFPR}_{\mathrm{Rural}}$. By testing the statistical significance of these correlations, we mathematically isolate the aggregate impact of socio-cultural features from the aggregate impact of economic and other features. We term the deduced framework so obtained as a 'Two-Factor Model'. In the fourth section, we show that the SDG 5 indicator "Female-to-Male LFPR ratio", when computed at state-level and for urban areas only, is a strong indicator of socio-cultural biases reducing FLFPR. Importantly, this indicator depends only on urban data. Applying a machine learning technique called clustering on this indicator, we cluster the states into three groups of states where each group consists of states similar to each other in terms of the impact of socio-cultural features on FLFPR. We validate the results of clustering by plotting known sociocultural factors across the three groups. In fifth section, we extend our analysis to FLFPR of rural virtual states. We use the sociocultural indicator to normalise (again a standard technique in machine learning) the FLFPR of rural virtual states and derive key insights on the effect of per capita income on FLFPR. Finally, we provide our inferences and conclusions.

Methodology and Results

Definitions and Data

We start by briefly introducing four concepts, namely, Fisher's Z-scores, K-means clustering, the curse of dimensionality and normalisation.

Fisher's Z-scores (or Fisher Z-transformation) is a method of converting Pearson's correlation coefficient r into a normally distributed variable z with a stable variance. z is given by the formula:

$$z = \operatorname{arctanh}(r) = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right)$$

The method is commonly applied for small sample sizes. It is used to compute confidence intervals for a Pearson correlation r as it enables more accurate confidence intervals and hypothesis tests where raw r fails.

K-means clustering is a machine learning algorithm that partitions a group of data into distinct and non-overlapping sub-groups (called clusters) based on their similarity. It works iteratively to minimise the distance between data points and their cluster centroids.

The curse of Dimensionality is a phenomenon that arises when data used for building a model is high-dimensional (keeping everything else the same, more data is required to train a model than available) leading to overfitting and spurious correlations, thereby reducing the efficiency and effectiveness of algorithms in discerning meaningful patterns or relationships in the data. To overcome the curse of dimensionality, techniques such as dimensionality reduction are routinely performed, where original data is transformed into smaller dimensions (or reduced number of factors/features) while still capturing the essence of the original features.

Data normalisation is a feature scaling technique that transforms data into a standard range, say between 0 and 1. This ensures that features with different scales or units contribute equally to the modeling/analytics work, which improves the performance of many machine learning algorithms. In general, for custom use cases (such as rural Female LFPR), normalisation with respect to another/second factor is performed not only to transform data into a standard range but also to control for extra parameters covered in the second factor. We next proceed to the key results.

We use the Periodic Labour Force Survey's 2023 round, the annual survey conducted by the National Statistical Office of India. This survey has been conducted since 2017–18 and provides estimates for the LFPR, unemployment rate, and other key employment indicators.

Differences in Urban and Rural FLFPR

We start by observing that the mean FLFPR for urban areas is distinct from the mean FLFPR for rural areas in a statistically significant manner. We find the mean and standard deviation of LFPR in Rural Male ($\mathrm{MLFPR_{Rural}}$), Rural Female ($\mathrm{FLFPR_{Rural}}$), Urban Male ($\mathrm{MLFPR_{Urban}}$) and Urban Female ($\mathrm{FLFPR_{Urban}}$) over the 29 states of India by using data from PLFS (2023) as shown in Table 1.

Table 1: Mean and Standard Deviation of LFPRs

	$\mathrm{MLFPR_{Rural}}$	$\mathrm{FLFPR_{Rural}}$	$\mathrm{MLFPR_{Urban}}$	$\mathrm{FLFPR_{Urban}}$
Mean	78.58	45.70	73.44	28.55
Standard Deviation	4.828197006	17.34777105	3.406425348	8.79579134

Source: Authors' analysis using PLFS (2023).

We design a two-tailed Hypothesis test with the null hypothesis formulated as follows:

$$H_0 : \mu_{\mathrm{FLFPR_{Urban}}} = \mu_{\mathrm{FLFPR_{Rural}}}$$

where $\mu_{\mathrm{FLFPR_{Urban}}}$ and $\mu_{\mathrm{FLFPR_{Rural}}}$ denote mean of $\mathrm{FLFPR_{Urban}}$ and mean of $\mathrm{FLFPR_{Rural}}$, respectively, and the mean is computed over all states. The pooled estimate of variance shall be

$$s_p^2 = \frac{\sigma_{RF}^2 + \sigma_{UF}^2}{2} = 189.16.$$

The relevant test statistic for t-test can be computed as:

$$t = \frac{(\mu_{\mathrm{FLFPR_{Rural}}} - \mu_{\mathrm{FLFPR_{Urban}}})}{s_p\sqrt{\frac{2}{n}}} = \frac{45.70 - 28.55}{(13.75)\sqrt{\frac{2}{29}}} = 4.75.$$

The t value at significance level $\alpha = 0.05$ and degrees of freedom $df = 29 + 29 - 2 = 56$ is given by $t_{0.05.56} = 2.005$. Since the test statistic $t > t_{0.05.56}$, the null hypothesis H_0 is rejected at 95% confidence level. Thus, $\mu_{RF_{LFPR}} \neq \mu_{RF_{LFPR}}$ at $\alpha = 0.05$.

We then consider two scenarios. In scenario 1, we cluster all FLFPR data points into two clusters, with the first cluster containing all 29 values of rural FLFPR and the second cluster containing all 29 values of urban FLFPR. The total dispersion observed with this grouping (that is, the sum of dispersion over both the clusters) is 378.31. In scenario 2, we cluster all FLFPR data points into the 29 clusters where each cluster corresponds to a given state and contains two data points (urban and rural FLFPR). In this scenario, the total dispersion is observed to be 3554.12. Combining the two observations, we get the results that (a) the means of rural FLFPR and urban FLFPR are statistically different; and (b) the total dispersion across two interstate clusters of rural and urban FLFPR data points is significantly smaller (that is 378.31) than the total dispersion of 3554.12 across 29 state wise clusters with each cluster containing two data points. Therefore, it is statistically established that for characterising FLFPR across states, the rural and urban FLFPR should be considered separately rather than combining them as a single state-level datapoint.

A Two-Factor Model for FLFPR

We develop a two-factor model for FLFPR which is inherently more robust to the curse of dimensionality than the state-level models in the existing literature. We start by focussing on the cross-correlation coefficients of the four LFPRs, that is, $\mathrm{FLFPR_{Urban}}$, $\mathrm{FLFPR_{Rural}}$, $\mathrm{MLFPR_{Urban}}$ and $\mathrm{MLFPR_{Rural}}$, across states. Once again, we take the data from PLFS (2023). The four relevant correlation coefficients (Karl Pearson's correlation coefficients) arrived at, and their corresponding Fisher's Z Score are given in Table 2.

Table 2: Cross Correlation Coefficients and Fisher's Z-Score

	ρ	Z- Score
$\mathrm{MLFPR_{Rural}}$, $\mathrm{FLFPR_{Rural}}$	0.372784764	0.391653435
$\mathrm{MLFPR_{Urban}}$, $\mathrm{FLFPR_{Urban}}$	−0.076364137	−0.076513097
$\mathrm{MLFPR_{Rural}}$, $\mathrm{MLFPR_{Urban}}$	0.65721785	0.787900184
$\mathrm{FLFPR_{Rural}}$, $\mathrm{FLFPR_{Urban}}$	0.597630494	0.689453018

Source: Authors' analysis using PLFS (2023).

We will now use Fisher Z- Test to show that the correlation of $\mathrm{FLFPR_{Urban}}$ is stronger with $\mathrm{FLFPR_{Rural}}$ than its correlation with $\mathrm{MLFPR_{Urban}}$. We begin with the null hypothesis:

$$H_0: \rho(\mathrm{FLFPR_{Urban}}, \mathrm{FLFPR_{Rural}}) \le \rho(\mathrm{FLFPR_{Urban}}, \mathrm{MLFPR_{Urban}}).$$

This is equivalent to the null hypothesis:

$$H_0: Z_{\rho(\mathrm{FLFPR_{Urban}}, \mathrm{FLFPR_{Rural}})} \le Z_{\rho(\mathrm{FLFPR_{Urban}}, \mathrm{MLFPR_{Urban}})}$$

in the corresponding Fisher's Z. We equivalently write

$$H_0: Z_1 \le Z_2,$$

where $Z_1 = Z_{\rho(\mathrm{FLFPR_{Urban}}, \mathrm{FLFPR_{Rural}})}$, $Z_2 = Z_{\rho(\mathrm{FLFPR_{Urban}}, \mathrm{MLFPR_{Urban}})}$.

The Z statistic is given by $Z = \frac{Z_1 - Z_2}{\sigma_{Z_1 - Z_2}}$, where $\sigma_{Z_1 - Z_2} = \sqrt{\frac{2}{n-3}} = \sqrt{\frac{2}{26}} = 0.2773$. Therefore, $Z = \frac{0.766}{0.2773} = 2.7624$. Also, the Z value with $\alpha = 0.05$ is $Z_\alpha = 1.645$. As Z statistic is $> Z_\alpha$, we reject the null hypothesis H_0. Therefore, there is a stronger correlation between $\mathrm{FLFPR_{Urban}}$, $\mathrm{FLFPR_{Rural}}$. In other words, the urban female LFPR exhibits a higher correlation with rural female LFPR than with urban male LFPR.

Motivated by the above mathematical result, we can develop the following results. Since the correlation between urban male LFPR and urban female LFPR is a negative number close to zero, it shows that though urbanisation is vital for economic growth, it is not impacting the male and female work force participation in the same way. In fact, the impact of urbanization on female work force participation is almost independent (or slightly opposite) of the impact of urbanization on male work force participation. Further, the strong positive correlation between female LFPR in both urban and rural areas implies that the state-level features which reduce the FLFPR are impacting the FLFPR in a similar way in both rural and urban areas. In the same manner as above, we can use Fisher Z- Test to show that the correlation of $\mathrm{MLFPR_{Rural}}$ is stronger with $\mathrm{MLFPR_{Urban}}$ than its correlation with $\mathrm{FLFPR_{Rural}}$. The strong positive correlation between $\mathrm{MLFPR_{Rural}}$ and $\mathrm{MLFPR_{Urban}}$ shows that there are factors which favour Male LFPR in both rural and urban states. These factors are not impacting female LFPR in the same way.

Given the above observations, we propose a two-factor model, as follows. We consider a linear model (like linear regression) where FLFPR is impacted by just two factors. The first factor F1 (a scalar decimal value) encapsulates all the impact of socio-cultural features which impact the Female LFPR but do not impact the male LFPR at all. The second factor F2 (again a scalar decimal) encapsulates the aggregate impact of all other factors (economic factors including urbanisation or any other factors). Mathematically, we may write $FLFPR = \mathrm{F1} + \mathrm{F2} + e$ where e could be irreducible error, to represent FLFPR in the Indian states. We emphasise that such a model is always possible in linear space if we restrict our analysis to linear model. This is a known mathematical result in the field of machine learning, where techniques such as Factor Analysis and Principal Component Analysis are routinely used to reduce feature/indicator space to a small number of factors. Also, note that F1 and F2 may not themselves be linearly related to their constituent features. Given that $\rho(\mathrm{FLFPR_{Urban}}, \mathrm{MLFPR_{Urban}}) \to 0$, we can infer that the urbanisation factors which should ideally impact $\mathrm{FLFPR_{Urban}}$ and $\mathrm{MLFPR_{Urban}}$ equally are rendered ineffective in the linear model by socio-cultural factor F1. Using the same reasoning, we can argue that not only urbanisation, but the entire F2 should impact $\mathrm{FLFPR_{Urban}}$ and $\mathrm{MLFPR_{Urban}}$ equally, and the only factor impacting the difference between $\mathrm{FLFPR_{Urban}}$ and $\mathrm{MLFPR_{Urban}}$ should be F1.

Consequently, the indicator *female-to-male LFPR ratio* (defined by Niti Aayog for SDG 5), if restricted to urban areas as

$$\alpha = \frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}$$

can be assumed to be statistically independent of the impact of the F2 (economic features including urbanisation or any other features) and to be statistically correlated with socio-cultural factor F1 in a linear and direct manner.

We emphasise that this is a very important result. This result allows — for our characterisation of state-level disparity in FLFPRs — to not only mitigate the curse of dimensionality but also establishes that the state-level indicator *female-to-male LFPR ratio for urban areas* or $\alpha = \frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR}}$ is linearly and directly correlated to the impact of socio-cultural factors F1. In other words, the ratio of Female-to-Male LFPRs in urban areas gives us a natural experiment (or natural AB test in machine learning terminology) where we can segregate the impact of socio-cultural features from economic and other features. We will use this idea to characterise the impact of socio-cultural factors on FLFPR across states.

While the above result (that Female-to-Male LFPR ratio is a strong proxy for socio-cultural norms across states of India) has been supported statistically and mathematically above, it is worth providing an economic interpretation for the above result.

Economic Interpretation of Urban Areas as Proxy for Socio-Cultural Norms

Urban areas provide a better proxy for analysing cultural influences on the female-to-male labour force participation ratio (FLFPR/MLFPR) because they reduce distortions arising from subsistence agriculture and family-based work that are common in rural economies. In rural India, relatively high female participation is often driven by economic necessity, unpaid family labour, and agricultural work, which can mask underlying socio-cultural constraints on women's employment.

In contrast, urban employment is more closely associated with formal wage work, mobility, and public interaction, making women's participation more sensitive to social norms, safety concerns, family expectations, and restrictions on women's autonomy. Despite greater educational attainment and broader employment opportunities in cities, urban FLFPR in India remains comparatively low, suggesting that socio-cultural barriers continue to significantly influence women's labour market participation.

Empirical studies complemented with the mathematical framework show that urbanisation does not automatically increase female employment in developing economies such as India. Instead, the gap between available opportunities and women's actual workforce participation highlights the importance of cultural norms, childcare responsibilities and safety concerns. Consequently, the urban FLFPR/MLFPR ratio serves as a more effective indicator of gender-based socio-cultural barriers and is useful for designing policies aimed at improving women's economic participation.

On the other hand, $\rho(\mathrm{MLFPR_{Rural}}, \mathrm{FLFPR_{Rural}}) = 0.4$ implies that the correlation between rural FLFPR and rural MLFPR is impacted by the interplay of both economic and socio-cultural factors. Therefore, if we normalise (a standard technique in machine learning) the rural data with the socio-cultural factors obtained from urban data, we get a method to characterise the impact of economic and other factors across state-wise FLFPR.

Relative Impact of Socio-Cultural Factors on State-wise Disparity in FLFPR

In this section, we first apply a clustering algorithm to group the 29 states of India on the basis of the impact of socio-cultural factors on reduction in FLFPR. We then analyse the groups so obtained and finally validate the grouping by plotting known socio-cultural features across the three groups.

We begin with finding a grouping of the states into clusters based on the state-level socio-cultural indicator (defined in the previous section):

$$\alpha = \frac{\mathrm{FLFPR}_{\mathrm{Urban}}}{\mathrm{MLFPR}_{\mathrm{Urban}}}$$

We use K-Means clustering for formulation of clusters. These results can be represented as the four clusters shown in Figure 1.

As we are filtering out the economic factors, each cluster comprises states which are similar in terms of dominance of socio-cultural factors. We label these clusters as:

1) High Socio-cultural index, which comprises the states in cluster 2 and cluster 0;
2) Medium Socio-cultural index, which comprises states in cluster 3; and
3) Low Socio-cultural index, which comprises states in cluster 1.

These three labels are visible in Figure 1. They will be referred to as group/label 1, 2, 3, respectively.

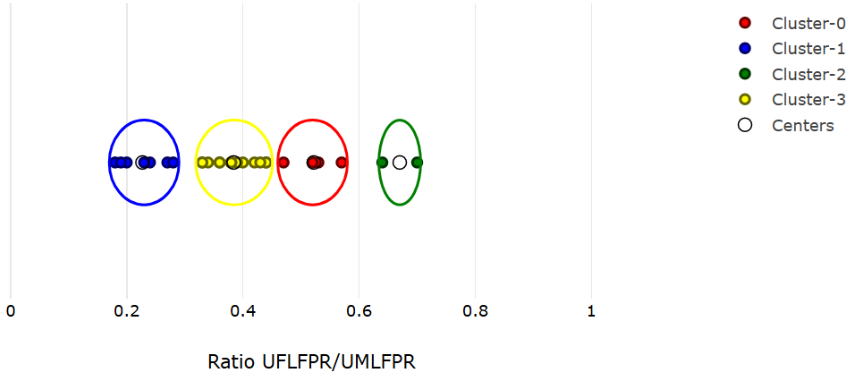

Figure 1: K-Means Clustering of States

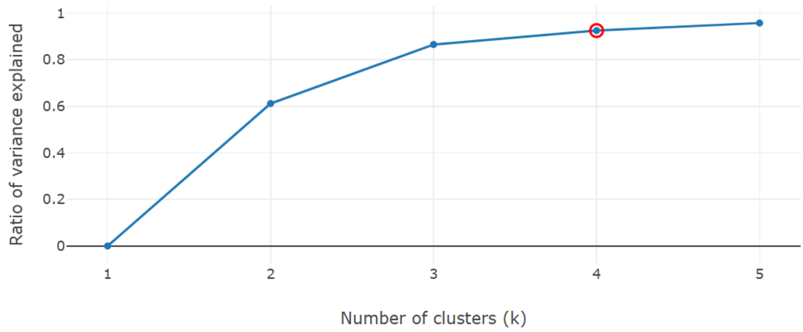

Figure 2: The Elbow Method for Optimal K

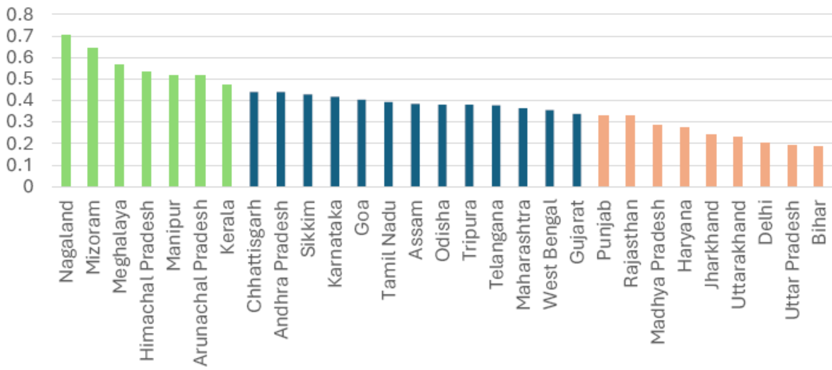

Figure 3: Clustering of States based on Socio-Cultural Factor

The states for which the ratio $\alpha \geq 0.47$, are labelled as 'High Socio-cultural index.' This comprises states like Nagaland, Mizoram, Meghalaya, Himachal Pradesh, Manipur, Arunachal Pradesh, and Kerala. These states have the highest ratio of the normalised FLFPR, filtering out the economic factors. The states for which the ratio $0.34 \leq \alpha < 0.47$ are placed in the label 'Medium Socio-cultural index'. These states include Chhattisgarh, Andhra Pradesh, Sikkim, Karnataka, Goa, Tamil Nadu, Assam, Odisha, Tripura, Telangana, Maharashtra, West Bengal, and Gujarat. The states with $\alpha \leq 0.33$ are placed in the label 'Low Socio-cultural index'. These states include Punjab, Rajasthan, Madhya Pradesh, Haryana, Jharkhand, Uttarakhand, Delhi, Uttar Pradesh, and Bihar. This clustering is particularly useful as it groups the states on the basis of dominance of socio-cultural factors, which can be a useful resource in tackling the problem of low FLFPR, which is driven by the social setup in India to a significant extent. We now further validate our findings by studying the effect of different socio-cultural factors like literacy rate, crime against women, children dependency on females in the three labels.

Validation of the Grouping with Comparative Box Plots

Literacy Rate and FLFPR

Literacy rate of women is an important feature affecting FLFPR. In the Indian context, literacy rate is linked with a U-shaped curve for female workforce (see Chatterjee et al (2018), DGE (2023)). Women with low literacy rate tend to participate more in the workforce, their participation in the workforce goes down when they reach a certain level of education and again goes up after reaching higher levels of education. However, not all states in India exhibit the expected trend in FLFPR. For instance, Kerala despite having high literacy rate has a falling FLFPR (see Mathew (2015)). To explain this dichotomy, we examine the FLFPR in our socio-cultural labels. We concentrate on adjusted Female Literacy Rate, that is, the ratio of Female Literacy /Rate Male Literacy Rate to maintain our focus on the socio-cultural factors. We formulate a comparative box plot for the three groups.

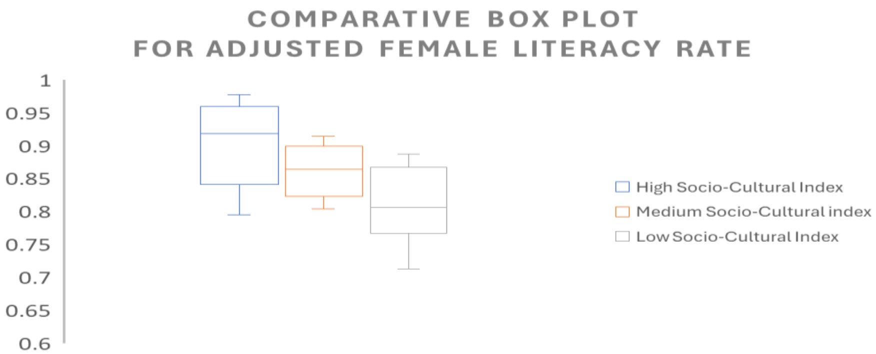

Figure 4: Comparative box plot on adjusted female literacy rate

Crime Against Women and FLFPR

Crime against women is a negative constraint on female workforce participation in India (Gupta 2023) and is believed to be a deterrent to higher female workforce participation. The crimes against women in our three socio-cultural groupings are analysed through Figure 5.

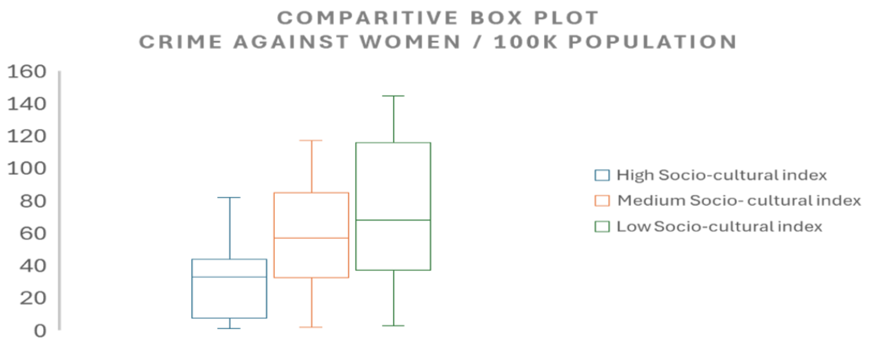

Figure 5: Comparative box plot on crime against women

The box plot shows that states with higher socio-cultural biases (or low socio-cultural index) have higher crime rates against women. The crime rate in the three labels is in sync with the extent of their socio-cultural biases.

Child Dependency on Females

A disproportionately high share of childcare responsibilities is borne by women in India. This is believed to be another factor driving lower workforce participation of women. The ratio of the number of children less than fourteen years of age in any state and the total number of females in that state, using data from CSO (2018), is used in Figure 6.

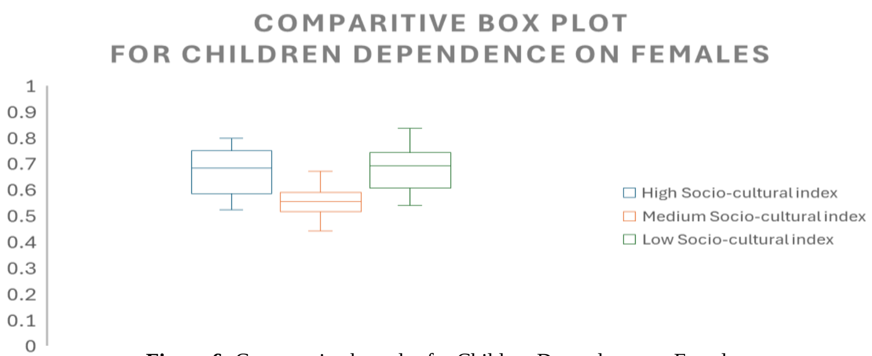

Figure 6: Comparative box plot for Children Dependence on Females

While the states with low socio-cultural index have the highest median child dependency ratio, the pattern between medium and high socio-cultural index states and child dependency is not clear.

In the above three analyses, we observed that the clustering of states based on socio-cultural indicator (Female-to-male LFPR ratio) captures the impact of two of the most well-known socio-cultural factors which reduce FLFPR, and partly the third socio-cultural factor, namely child dependency.

Discussion and Conclusion

While the disparity in state-wise Urban FLFPR is better captured through $\alpha = \frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}$ and is primarily dominated by socio-cultural factors, the effect of socio-cultural factors is less pronounced in the rural virtual states. The commonly accepted view is that the household income in the rural regions is on the lower side, and hence, the women step in to meet the household expenses. This results in relatively greater workforce participation of women in rural regions than urban regions. Thus, the rural regions see an interplay of both economic and socio-cultural factors. In order to focus only on the economic factors, we consider the ratio

$$\frac{\frac{\mathrm{FLFPR_{Rural}}}{\mathrm{MLFPR_{Rural}}}}{Median\,\frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}}$$

for each of the three groups of states defined in the previous section to normalise the data for $\mathrm{FLFPR_{Rural}}$. In particular, the $Median\,\frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}$ for each group is a representative of Socio-cultural factors in that group, and hence, the resultant normalised $\mathrm{FLFPR_{Rural}}$ represents the impact of the economic and other factors in that cohort.

The intuition behind the approach may be seen in the following manner. The primary reason for normalisation is to bring different features and factors to a uniform scale and make the ratios comparable. Critically, the second reason for normalisation is to control for factors or features which are common to both numerator and denominator so that we can derive inferences related to a specific aspect without polluting the inference due to extraneous factors. As an example, in the Female-to-male LFPR ratio we can cleanly focus on factors related to female LFPR, as the common factors impacting both female and male LFPR are almost cancelled out. Similarly, in the normalisation above, the denominator $Median\,\frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}$ already and significantly captures the impact of socio-cultural factors which are common in urban and rural areas of the state. In other words, through the normalised ratio

$$\frac{\frac{\mathrm{FLFPR_{Rural}}}{\mathrm{MLFPR_{Rural}}}}{Median\,\frac{\mathrm{FLFPR_{Urban}}}{\mathrm{MLFPR_{Urban}}}}$$

we can cleanly focus on the factors related to economic factors (such as development) impacting Female LFPR in the rural areas and hence should be in alignment with the global literature where we find that Female LFPR decreases (in the initial stages of development) with increasing per capita income.

To validate this inference, we plot this normalised $FLFPR_{Rural}$ against the household income data from a different data source, NABARD (2022), in Figure 7.

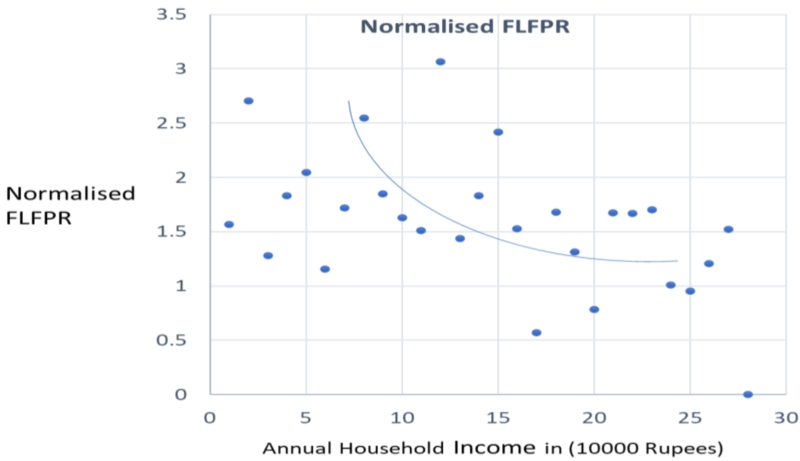

Figure 7: Normalized FLFPR

The normalised FLFPR curve, the asserted representation of the impact of economic factors on FLFPR in the two-factor model, is high where the household income is low and low where the household income is higher. However, the household income must rise substantially for us to get a complete U in the FLFPR graph. This shows that when we remove the socio-cultural factors, the $FLFPR_{Rural}$ rises and falls in the usual expected way. The unexpected behaviour of $FLFPR_{Rural}$ is mainly attributed to the social biases in the different cohorts.

As far as statistical analysis is concerned, it is better to model FLFPR separately for rural and urban parts of each state than to model directly at the combined state level. The statistical correlations across LFPRs of Urban Females, Urban Males, Rural Females and Rural Males and results from the hypothesis testing argue that the SDG 5 indicator defined by Niti Aayog as *Female-to-Male LFPR ratio*, when restricted to urban areas, is an excellent indicator of the impact of socio-cultural factors on reduction in Female LFPR at the state level. Using this indicator, we grouped the states of India based on socio-cultural biases against women rather than grouping them on the basis of geography as is the norm in the existing literature.

The novel grouping of states appears sensible and is validated by its correlations with the known sociocultural biases such as female literacy rate, crime rates against women and child dependency ratio per female. Finally, we extended the analysis to FLFPR for rural parts of the states. On observing the data for per capita income in urban states and rural states, we assess that the urban states fall in the lower-middle-income group and the middle-income group (in purchasing power parity) when compared to per capita income in developed/ rich economies of the world. However, the rural regions in many states fall in the lower-income group. This understanding encourages us to believe that the U-shaped Curve for FLFPR in rural states would be on the higher side, as survival instinct drives women towards work, while the graph for FLFPR in the urban regions would be on the lower side as women withdraw from the workforce when the family income reaches a certain level. However, we may not get a complete U as the female income and education must rise substantially for increased female participation in the workforce.

We also note that the methodology adopted for analysing the FLFPR in urban regions cannot be the same as the methodology that one may adopt for the rural regions. The reason for this is that the socio-cultural factors are more pronounced in the urban regions than the rural regions owing to the difference in income level in these regions. In the urban regions, we understand the impact of various socio-cultural factors on the three state clusters. However, in the rural states, the FLFPR is impacted by both economic factors as well as socio-cultural factors owing to the low income in rural regions. On normalising the data on female LFPR in rural regions, we can clearly see a U-shaped curve for FLFPR with respect to household income in rural regions, similar to the ones observed in the other parts of the world.

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