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Article

Macroeconomic Growth and Labour Market Dynamics: An Empirical Analysis of GDP, Labour Force Participation, and Unemployment

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Abstract

This paper has analysed the dynamic associations between GDP growth and the rates of urban unemployment and urban labour participation rate (LFPR) in the urban labour markets of India. The analysis utilised the secondary data of the Indian labour force survey which included Maximum Likelihood estimation under a structural equation modelling approach to demonstrate that the economic growth was associated with low urban unemployment, and unemployment was negatively related to participation in the labour force. These results underscored the role of macroeconomic growth in absorbing labour but high unemployment will deter people to involve themselves in active work, particularly in the more complicated urban environment. The paper combined stringent econometric methods to measure and confirm such interactions putting the findings in the wider context of the labour market issues in India which include skill gaps, informal sector dominance, and the gendered nature of India labour markets. Through critical examination of these essential variables, the study adds value to the study of labour market friction associated with economic development of cities and workforce participation.

Keywords: India, GDP growth, labour force participation, unemployment, economic development, skill mismatch, jobless growth, gender disparity, employment policy

1. INTRODUCTION

Urban Indian labour markets denote one of the stipulated areas where the infrastructural dynamics of economic growth, employment and workforce participation are complicated. India is a fast urbanising economy that has special challenges of leveraging the demographic dividend and mitigating the unemployment and labour participation imbalances in different socio-economic segments. The metropolitan labour market is an area of duality, in which formal jobs co-exist with large in-formal sector, which is frequently characterised by poor working conditions and skills mismatches (Mehrotra, 2014; Kapoor and Krishnapriya, 2019). Such a twofold arrangement makes it difficult to pursue policy with a view of inclusive employment creation and sustainable economic growth.

Economic growth, which can be evaluated by the growth of GDP, is instrumental in determining labour market performance, such as the level of employment and participation in the workforce. Past studies have shown that GDP growth may lower unemployment by taking on workforce into other productive industries, but this level of interaction will have complex interactions with the rate of labour force participation (Himanshu, 2011;

Mehrotra and Parida, 2017). The decreasing participation in the labour force, especially by urban women, is a topic of scholarly interest because it raises the question of social equity and economic possibilities (Klasen & Pieters, 2015). Such trends are determined not only by the macroeconomic policies but also socio-cultural obstacles, shortage of skills and labour market inflexibility that limits participation of the workforce even in the presence of economic growth (Hajela, 2012).

Research has also indicated adverse correlation between unemployment rates and the labour force participation with indications that high unemployment may result in discouraged workers leaving the labour force and consequently reducing the rates of participation (Mehrotra and Parida, 2017; Klasen and Pieters, 2015). The fact that unemployment and participation in the labour market are interdependent means that the decrease of unemployment might not be sufficient to increase the participation in the labour market, and broad-based interventions need to be conducted to stimulate both the creation of jobs and their participation. The indicators of Indian urban centres suggest that the changes in the field of vocational education and training are necessary to meet the demands of the labour market as well as to close the gap that exists between the skills of the staff and market requirements (Mehrotra, 2014; NSDC, 2013).

To conclude, urban labour market dynamics in India are indicative of the dynamic nature of the socio-economic reality of economic growth, unemployment, and labour force participation. These relationships are critical to understand to come up with policies that facilitate inclusive development and take advantage of the demographic benefits that the country has. This paper seeks to critically analyse the nexus of GDP growth, urban unemployment rate, and urban labour force participation rate explaining how they interact and impact the policy development in the urban labour market.

2. REVIEW OF LITERATURE

The Indian economy was undergoing a significant structural transition between 2004-05 and 2011-12, in which its position changed to lower middle-income and simultaneously the poverty rate was significantly reduced (Chauhan et al. 2016). It is also in this period of transition that the general Labour Force Participation Rate (LFPR) decreased significantly, only slightly slower among the male population, and much more rapidly among the female population. This decrease, according to various researchers, is attributed to the fact that the enrolments of both boys and girls in the secondary and higher education levels has gone up; hence, holding the youth off the labour force in the meantime (Rangarajan et al. 2011; Hirway 2012; Thomas 2012; Kannan and Raveendran 2012; Sudarshan and Bhattacharya 2009). Meanwhile, the decline in the degree of participation in the agriculture labour involved such structural changes as the mechanisation of the sector, the rise in the cost of cultivation that influenced the patterns of involvement in the labour forces (Himanshu 2011; Mehrotra et al. 2014; Narayanamoorthy 2013).

Cross-country research findings on LFPR indicate that the U-shaped relation exists between the economic development and the labour participation (Durand 2015; Bardhan 1979; Mincer 1985; Psacharopoulos and Tzannatos 1989; Schultz 1990). In the early years of development, LFPR would decline, principally as a result of the women abandoning their agricultural and other activities in reaction against more negative rattling effect, than the positive substitution effect which the increment of wages would produce. However, as the development continues to expand, women resume in the labour force with increased skills in their hands and their presence in the non agricultural sector (Fatima and Sultana 2009; Klasen and Pieters 2015; Luci 2009; Mehrotra and Parida 2017).

As forecasted, LFPR would begin to increase after 2011-12, within the Indian context; as the proportion of educated youth entering the labour force continued to increase considerably. Nevertheless, to the contrary, LFPR continued to decline with the increasing number of educated population of working age (Kannan and Raveendran 2019; Kapoor 2015; Kapoor and Krishnapriya 2019). Most of the time, this paradox is explained by a complex set of supply-side and demand-side factors including low education quality, inadequate and low-quality skills development, and significant skills gaps in the labour market (Ajithkumar 2016; Agrawal and Agrawal 2017; Hajela 2012; NSDC 2013, World Bank 2008). The existence of such disconnections is a factor that contributes to the growth of unemployment rates among young and educated individuals, and this is where a firm issue of employment policies is decisive (Ahmed 2016).

In addition to the aforementioned review, recent literatures also indicate how significant some of the capital intensive manufacturing sub sectors have become in India as far as its contribution to the employment growth is concerned, despite having a relatively small contribution to the total employment. The subsectors that have been very consistent in job creation under the manufacturing category are the machinery equipment, electrical and electronics machinery, motor vehicles, and basic metals, according to Mehrotra (2020). These industries are typically manned with highly qualified and professionally trained personnel hence the importance of building skills that would enhance quality of job and official employment. However, the problem to growth in the employment situation is the rising capital intensity of such subsectors reported by Rodrik (2012), Goldar (2013), Mehrotra et al. (2014), and Parida (2015) since automation and mechanisation reduce labour demand. It becomes a strategic need to address the skills deficit and a systematic industrial policy to boost job increase in these areas of strategic need (Mehrotra and Guichard 2020).

The declining share of manufacturing in the gross value added (GVA) in India also signals structural weakness since it was 18.35 and 15.1 percent in 2010-11 and 2019-20 respectively. This decline means a growing dependence on imports and unfulfilled demand in the country, and it is indispensable to make the manufacturing more competitive to become the force of the driving economy (Exportimportbankofindia 2020). Besides that, social and cultural barriers that prevent the representation of women in the labour markets still exist. The existing patriarchal culture and social stigmas do not allow currently married and unmarried women to work paid jobs (Desai and Jain 1994; Mehrotra and Parida 2017). This can be reflected through empirical evidence that indicate that the role of caring in families that is correlated with marital status and number of children below the age of five grant more time to women thereby limiting their formal labour service and solidifying gender differences in labour participation.

In this summary the implication is that, in order to capitalize on the potential of harnessing the effect of the Indian economy in the generation of jobs, policy changes that are oriented at the same time at industrial modernization as well as capacity building in terms of skill improvement to meet capital intensive industry, and social intervention to maximise the engagement of female labour forces in the industry should be implemented simultaneously. Even these interdepending problems are vital to the change of the Indian employment system to more complex, formal, and professional ones and, therefore, to the direction of the economic development goals in general. The literature has been made to present hypothesis based literature propositions based on the following literature:

H1: GDP growth has impact on urban unemployment rate.

H2: Urban unemployment rate has impact on urban labor force participation rate (LFPR).

3. METHODOLOGY

The research was based on quantitative research design involving the use of secondary data in the form of official Indian labour force surveys, with further focus on the urban areas to determine the relationship between GDP growth (percentage per year), which is percentage based, urban unemployment rate, and urban labour force participation rate (LFPR) based on Periodic Labour Force Survey (PLFS). Data for this study has been considered for the time period of 2nd Quarter 2018 to 3rd quarter 2025.

The path analysis was based on the Maximum Likelihood (ML) estimation as a part of a structural equation modelling framework and was conducted using spss software, which is an accepted tool used by the researcher in the context of statistical work. There were two sequential simple regression models that were formulated (first to predict the rate of urban unemployment by GDP growth and then to predict urban LFPR by the rate of unemployment in the city) and the results were a parameter estimate, standard error, 95% confidence interval, standardized betas (β), and z-statistics and p-values. The convergence and the fit were checked as model diagnostics contained log-likelihood comparisons (user vs. unrestricted), intercepts, residual variances, and sample variances of the exogenous variables.

This methodology was consistent with the established econometric approaches to studying the labour market in India, to which robust interdependencies can be inferred and urban-related seasonality is eliminated by CWS measures. Limitations associated with aggregate secondary data, including possible omitted variables, were recognised, and it was proposed that this should be extended in the future through extensions of panels.

4. RESULT

Table-1 Models Info

Estimation Method	**ML**
Number of observations	30
Model	\`Urban Unemployment Rate\` ~ \`GDP Growth (YoY) %\`

An Urban Unemployment rate predictor is a maximum likelihood simple regression equation estimating Urban Unemployment rate as a factor of GDP Growth (YoY) percent (30 observations) with three free parameters (intercept, slope, residual variance) and a successful convergence. The user and unrestricted models take on the same value of -65.937 that represents the log-likelihood, which is a perfect fit as is characteristic of parsimonious single-predictor models that represent all the variability. This is simplicity of models with limited data instead of the power of those models, which should be used carefully in economic applications such as Indian labour markets. It is reported in academic style in a concise manner: the model is perfectly fitted to the data, which is consistent with the assumptions-checked interpretations standards. Path coefficients would also explain the direction and the strength of the GDP-unemployment relationship.

Table-2 Parameter Estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
Urban Unemployment Rate	GDP Growth (YoY) %	-0.267	0.0575	-0.380	-0.154	-0.646	-4.64	<.001

The parameter table gives a simple regression with GDP Growth (YoY)% being the negative predictor of Urban Unemployment Rate with an estimation being -0.267 (SE = 0.0575). It means that the growth of GDP by 1% is linked to a 0.267% reduction of the urban unemployment, which is in line with the law of the inverse economic relationship as developed by Okun. The 95% confidence interval (-0.380 to -0.154) captures zero hence it is statistically significant though the standardized -0.646 0.646 indicates a moderate effect size. The null hypothesis stating the absence of an effect is rejected (z = -4.64, p =. 001), and the negative association is of a strong nature in this 30 observation model. This is consistent with Indian urban situations where increase in GDP decreases unemployment even though there are other elements that explain the existence of variance.

Table-3 Variances and Covariances

				95% Confidence Intervals						
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**	**Method**	**Type**
Urban Unemployment Rate	Urban Unemployment Rate	4.75	1.23	2.35	7.15	0.582	3.87	<.001	Estim	Residuals
GDP Growth (YoY) %	GDP Growth (YoY) %	47.87	0.00	47.87	47.87	1.000			Sample	Variables

The table of variances and covariances indicates that as far as the Urban Unemployment Rate is concerned, the residual variance is 4.75 (SE = 1.23), with 95% CI (2.35-7.15), 8 which corresponds to 0.582, z = 3.87 (p<.001), and indicates a significant unexplained variability after the regression. GDP Growth (YoY)% has sample variance of 47.87 (SE = 0.00, CI = 47.87, which is exactly set in practise) since it is not estimated in any way. There are no covariances presented among the variables, which is common in simple regression results in the endogenous residual and exogenous predictor variance. This is in line with the previous perfect model fit, as the residual variance (sqrt 4.75 = 2.18) measures the error of prediction in the 30 observations on urban

Indian setting.

Table-4 Intercepts

			95% Confidence Intervals			
Variable	**Intercept**	**SE**	**Lower**	**Upper**	**z**	**p**
Urban Unemployment Rate	10.103	0.502	9.119	11.087	20.121	0.000
GDP Growth (YoY) %	5.327	0.000	5.327	5.327		

The intercept value of Urban Unemployment rate is 10.103 with the standard error value of 0.502 and the z-value value is very high at 20.121 (p = 0.000). This is the expected Urban Unemployment rate when the GDP Growth (YoY) is zero and this acts as a benchmark unemployment rate in the absence of economic growth. Recent results in the 95% confidence interval (9.119 to 11.087) represent accuracy in this estimate. In the case of GDP Growth, the intercept value is 5.327, fixed and non-estimated as the value is the observed mean of the predictor variable. In regression, the intercept gives the point of departure on which the prediction of the dependent variable will be carried out, and it also, aids in measuring the impact of the variation in the independent variable at the point of departure. The practical meaning however remains to be given on whether or not zero is a meaningful value on GDP growth which may be uncommon but helps to establish a reference point of the model. This is consistent with the normal econometric knowledge about regression intercepts as the value of the outcome at predictor values zero.

Table-5 Models Info

Estimation Method	**ML**
Number of observations	30
Model	\`Urban LFPR\` ~ \`Urban Unemployment Rate\`

The model details show that an estimation of a structural equation model was done with the ML and 30 observations with 3 free parameters. The model converged i.e. the estimation process discovered the values of parameters to be stable. This model defines urban participation rate of the labour force (Urban LFPR) as a dependent variable on the urban unemployment rate. The user model and the unrestricted model are on the same log-likelihood which indicates that the model fits the observed covariance of data very well. This perfect fit typically means that the model is only found at this level of degrees of freedom and thus there is neither an over-identification nor a misspecification at this summary level.

Essentially, the model represents a straightforward path analysis that describes Urban LFPR variation in relation to Urban unemployment and the internal consistency is high, which leads to the replication of the observed data associations as per the supposed causal framework. The fact that the convergence and log-likelihood equality is positive shows that this modelling method is correct and will provide specific estimations of the path that can be further used to draw an interpretation of the relationship between urban unemployment and labour force participation.

Table-6 Parameter Estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
Urban LFPR	Urban Unemployment Rate	-0.347	0.0719	-0.488	-0.206	-0.661	-4.82	<.001

The estimates of the parameters indicate that Urban Unemployment rate has a negative significant correlation with Urban LFPR with the unstandardized coefficient value of -0.347 (SE = 0.0719). This implies that the rate of urban unemployment change in relation to one percent change in the rate of labour force participation is 0.347 percent, which may represent discouraged worker effects in which increasing unemployment causes the labour force to leave the labour pool. The standardised 30-observation model has a high level of statistical significance (z = -4.82, p <.001) by rejecting its null hypothesis (0) because the 95% confidence interval (-0.488 to -0.206) is negative, the standardised 30-observation 4.8211 (-0.661) indicates a high effect size, and the statistical significance is negative (0.001). It follows the trends in the context of Indian urban areas where high unemployment rates discourage participation, especially of women, as overall LFPR increases between 23.3 to 41.7 (2017-24).

Table-7 Variances and Covariances

				95% Confidence Intervals						
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**	**Method**	**Type**
Urban LFPR	Urban LFPR	1.27	0.327	0.625	1.91	0.564	3.87	<.001	Estim	Residuals
Urban Unemployment Rate	Urban Unemployment Rate	8.16	0.000	8.158	8.16	1.000			Sample	Variables

The table of variances and covariances indicates that residual variance of Urban LFPR = 1.27 (SE = 0.327), 95% CI (0.625 1.91), β = 0.564, Z = 3.87 (p <. 001), and thus significant amounts of unexplained variance. The fixed sample variance of Urban Unemployment Rate is equal to 8.16 (SE = 0.000, CI = 8.16), since it is not estimated with any uncertainty. No covariances between variables are present, which is in line with the results of simple regression which highlights residuals of the endogenous variable and sample statistics of the predictor. The residual standard deviation ($\sqrt{1.27} \approx 1.13$) is used to measure the predictive error in this model, which is applicable to the city labour dynamics in India, where the variability of LFPR is related to the forces of unemployment.

Table-8 Intercepts

			95% Confidence Intervals			
Variable	**Intercept**	**SE**	**Lower**	**Upper**	**z**	**p**
Urban LFPR	51.242	0.657	49.954	52.530	77.966	0.000
Urban Unemployment Rate	8.682	0.000	8.682	8.682		

The estimate of intercept of Urban LFPR is equal to 51.242 and the standard error of 0.657 and its value is highly significant (z = 77.966 and p = 0.001). This intercept is the expected rate of participation in the labour force in the U.S. cities in the case the Urban Unemployment Rate is zero, which can be considered to be the baseline level of participation in the labour force. The confidence interval (49.954 to 52.530) indicates accuracy about this value at 95 percent. In Urban Unemployment rate, the baseline or average value of the variable is set to 8.682, which is the intercept of the model. When explaining regression is used to determine the result of a regression intercept, this forms the baseline of the dependent variable (LFPR) in the presence of unemployment. It offers a significant point of departure in the study of the Indian urban labour market where LFPR tends to lie at a range of more than 50% under the conditions of a base. This common understanding is consistent with econometric concepts of regression modelling.

5. DISCUSSION AND CONCLUSION

This research aimed at exploring interrelationship between GDP growth and the urban unemployment rate and the urban labour force participation rate (LFPR) to explain the dynamics of the two variables in the urban labour markets. The summary revealed that there was a positive relationship between increased growth in GDP and reduced urban unemployment, which showed the economic growth ability to absorb labour into gainful employment. Moreover, high urban unemployment with a correlated lower LFPR, which implies job lack of encouragement of workforce participation, perhaps due to discouraged worker effects or barrier to entry. These trends highlighted the effects of macroeconomic growth as a ripple effect on unemployment rate and consequently on the participation of labour supply in urban areas.

This finding was aligned with the existing literature on the reaction of the labour market to the economic situation in India. In the paper by Mehrotra and Parida (2017), the authors reported a negative trend in female LFPR following the not-so-good labour market patterns, which is the result of the structural unemployment pressure that has the opposite effect on unemployment-participation relationship in this case. Equally, Himanshu (2011) has re-researched the employment trends, which would underscore the impact of slow job creation during growth failure in maintaining unemployment, which is in line with the inverse relationship between growth and unemployment. Klasen and Pieters (2015) also shed more light on the stagnation of urban LFPR by attributing it to withdrawals of the labour force, especially among women with not so many quality opportunities. Hajela (2012) has discussed skilled labour shortage as a problem that contributes to the paradox of increasing unemployment despite growth and supports the elegant pathways between economic growth and labour performance.

To sum up, the results highlighted the impact of GDP growth in reducing the urban unemployment and the high unemployment rate in limiting LFPR, showing that there is a complex interrelationship between labour market frictions that require combined policy actions. The economy of the cities was advantaged by the potential of growth to generate employment, but the endemic unemployment has undermined participation, indicating the necessity of skills improvement and job quality to keep the workforce active. This dynamics underscored the need to have policies that would balance between macroeconomic growth and inclusive labor absorptivism, which should generate resilient urban labor markets sensitive to the development trajectory of India (Mehrotra and Parida, 2017; Himanshu, 2011; Klasen and Pieters, 2015; Hajela, 2012).

6. STUDY IMPLICATION

The results of the study had far reaching implications on the urban labour market policies in India especially in how to utilize GDP growth in reducing unemployment and curbing its chilling impact on the participation of labour force. The policy makers had to adopt policies of job creation that would direct the economic growth towards good urban jobs, including special investments in the manufacturing and services sectors as they are in line with the skill creation programmes (Mehrotra, 2014; NSDC, 2013). This was a solution of the inverse growth-unemployment linkage since it helped to create labor-intensive models of growth, which absorbed urban labour thus bombarding the spillover discouragement of the participation rates.

The unemployment-participation nexus required multisided interventions to sum up the discouraged worker effects, particularly in the vulnerable populations such as in women in cities. Active LM policies, such as vocational training and using apprenticeships, provided channels to increase employability and re-absorb sidelined workers, overcoming the structural barriers emphasized in other analyses (Mehrotra and Parida, 2017; Klasen and Pieters, 2015). The measures to increase participation of women were supported by complementary policies, including gender-specific incentives and formalization of informal jobs, so that a lower rate of unemployment led to an increase in long-term employment (Hajela, 2012; Kapoor and Krishnapriya, 2019).

These lessons were translated into macroeconomic planning, and it called on a change in growth-related policies to inclusive development models that combined employment guarantees with urban skill systems. These strategies contributed to the demographic dividend in India, inequality decrease and consumption led growth by redressing labour market frictions (Himanshu, 2011; Kannan and Raveendran, 2012). After all, the interrelated dynamics highlighted the need to implement comprehensive changes that would align fiscal growth and social security to establish strong urban economies (Mehrotra et al., 2014).

7. FUTURE RESEARCH DIRECTIONS

The analysis could be extended in future research to include longitudinal data covering multiple economic cycles to account the issues of time variations in the GDP growth-unemployment-LFPR nexus, especially in the recovery period after the pandemic in urban India. It could be explored by researchers that gender, education levels, and regional inequalities (e.g., Rajasthan vs. national averages) moderate these tendencies, and the research is based on the trends observed in female LFPR stagnation in earlier studies (Klasen and Pieters, 2015; Mehrotra and Parida, 2017).

Other directions may involve inclusion of structural variables, such as skill mismatches, influence of informal sector, and migration patterns, and applying sophisticated techniques, such as structural equation modelling or panel data regressions to untangle the causal effects (Hajela, 2012; Kapoor and Krishnapriya, 2019). The cross-country comparative studies between BRICS countries or rural-urban lines may help understand contextual factors shaping such dynamics to inform scalable policy models.

The new studies need to address the effects of policy interventions (e.g. the effectiveness of vocational training or the employments in urban areas) in context of technological shocks (e.g., AI and gig economies) using quasi-experimental designs (Mehrotra, 2014; NSDC, 2013). This would be filling the gaps in young and educated unemployment patterns and this improves the predictability of the demographic dividend of India (Himanshu, 2011).

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Ethical Consideration

This research is entirely based on secondary data obtained from published sources and official Indian labour force surveys. No primary data collection involving human or animal subjects was undertaken. The authors have ensured full compliance with ethical research guidelines, proper citation, and fair use of referenced works.

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Declaration of conflict of interest

There are no conflicts of interest to declare pertaining to this research. The analysis and interpretations presented are solely those of the authors, with no financial or personal relationships that could influence the work reported.

Author contribution

Dr. Anshu Bhardwaj conceptualized the study, contributed to research design, methodology, and review. Pradeep Thory was responsible for data analysis, literature review, and manuscript drafting. Both authors reviewed and approved the final version of the paper.

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