DVARA RESEARCH

Determining Optimal Credit Allocation at a District Level

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Abstract

In this paper, we attempt to develop a granular understanding of the relationship between credit (as measured by total bank credit outstanding in a district) and economic growth (as measured by Gross District Domestic Product) for 32 districts of Tamil Nadu. Analysing data for these districts from 2004-05 to 2011-12, we compute the output elasticity of credit depth at the district level, while controlling for exogenous factors such as rainfall, infrastructural development and other factors. We find that the responsiveness of output to changes in credit depth vary widely from district to district. Taking this into consideration, this paper provides a novel methodology for decision-making on optimal credit allocation towards districts. This could enable policy-making bodies such as RBI and NABARD to identify districts with excessive and deficient levels of credit depth and can also inform district-level interventions.

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1. Introduction

The role of financial sector development in a country's economic growth has been much studied and debated. On the one hand, development of financial institutions and markets has been touted as contributing to the economic growth process[1]. On the other hand, unrestrained and unchecked use of financial instruments and practices has been held responsible for macroeconomic crises[2]. A better understanding of the links between financial sector development and economic growth would have positive implications for policy making[3]. It is in this context that the question of financial sector development of India is considered in this paper.

While India has a deep history of policy making aimed at providing and improving access to formal financial services, large swaths of India remain unbanked - despite the recent nationwide roll-out of the Pradhan Mantri Jan Dhan Yojana that is expected to have covered 100% of Indian households, only 42% of adult Indians are active bank account holders[4] . Specifically with respect to delivery of formal credit, banking sector policy has focused efforts on expanding access to credit to rural and excluded regions, individuals and sectors for a number of decades. While considerable progress has been made, the extent of exclusion is still vast, and even in included sectors, segments and regions, the supply of credit has been characterized by scheduled commercial banks as the preeminent channel of credit delivery. While India as a whole has a credit-to-Gross Domestic Product (GDP) ratio or credit-depth (as it would be referred to in this paper) of about 58.6%[5] , for agriculture at less than 38%[6] it is even lower[7] , indicating poor outreach of formal credit to the sector despite all of the policy priority that has been given to it through Priority Sector Lending policies of the Reserve Bank of India (RBI)[8]. There are also large regional imbalances in credit depth. States such as Bihar have an overall credit to GDP ratio of less than 16% despite the fact that it has one of the lowest levels of GDP in the country. During 2007-2012, 38% of agricultural credit was accounted for by the Southern States despite them constituting less than 20% of India's Gross Cropped Area while the Eastern and North-Eastern states accounted for only 8%, despite having comparable Gross Cropped Area. Central India received only 13% of agricultural credit with 27% of Gross Cropped Area[3]. Similar variations can be observed for other sectors as well. Historically, policy interventions have been prone to consider Indian states as homogenous entities. However, with more evidence of regional and sectoral disparities, some policy interventions have been introduced to bring down such disparities. One such intervention is the annual exercise on preparing a Potential Linked Credit Plan (PLP) for each district that NABARD undertakes under the aegis of the Lead Bank Scheme laid out by the RBI. The PLPs are considered as *"a step towards decentralized credit planning with the basic objective of mapping the existing potential for development through bank credit. PLPs take into account the long term physical potential, availability of infrastructure support, marketing facilities, and policies/programs of Government and so on"*[4]. The RBI Committee on Comprehensive Financial Services for Small Businesses and Low Income Households[5] recommended *"moving to a new framework in which two parameters: District level credit depth, and sector and sub-sector level credit depth be used to determine the sector, sub-sector, and regional weights which are published every three years. Using these weights, banks would be required to reach an Adjusted PSL target of 150% of ANBC"*.

In this paper, we advocate a method or a class of methods which look at disaggregated growth responsiveness or output elasticity to credit. A more nuanced credit allocation approach using elasticity based weighting scale to apportion credit to different districts would help direct credit to the most productive regions and sectors. In this paper, we propose an optimal design for deriving the district specific weights to inform the regional credit allocation process (which can be further improved to include region-sectoral credit allocation). Through this paper, we attempt to understand what the nature of such a relationship is, between financial depth and economic development at a sub-national context, namely for the districts of Tamil Nadu, a southern State of India, and to develop a methodology for decision-making regarding how much credit must be targeted at a district level as a policy prerogative. Although, typically considered one among the most prosperous states in India, there exists significant variation in both the supply of credit and in growth of output between the different districts of the state[6]. The paper is divided into the following sections. Section 2 covers a review of existing literature for the context of the question we are seeking to answer. Section 3 covers data and methodology. Section 4 enlists the different estimations done and their empirical results, while Section 5 and 6 deal with policy interventions that can be considered with conclusions and future steps.

2. Related Work

Given the vastness of literature on the relationship between financial development and economic growth and its implications at a sub-national level, we summarize some of the key findings in existing literature which we hope to address in our work:

The relationship between financial development, economic growth and macroeconomic stability is non-monotonic and dependent on the time horizon

The earliest school of thought, led by Joseph Schumpeter[7] posits that financial development drives technological innovation and consequently, the rate of economic growth. The second school argues that economic growth generates demand for particular financial products, leading to the creation of a well-developed financial sector[8]. However, recent empirical economic evidence across a cross-section of 80 countries over the time period 1960-1989 shows that higher levels of financial development are significantly and robustly correlated with faster current and future rates of economic growth, physical capital accumulation, and economic efficiency improvements. In other words, when countries have relatively high levels of financial development, economic growth tends to be relatively fast over the next 10 to 30 years. A deeper financial system is significantly associated with less growth volatility; however, the relationship appears to be nonlinear[9]. As the financial system becomes larger relative to GDP, the increase in risk becomes relatively more important, and acts to reduce stability. In other words, when there is excess credit within an economy, there can be a vanishing effect of financial depth on economic growth. A study analyzing the relationship at cross-country level yields that the threshold above which this vanishing effect occurs is estimated to be when private credit goes beyond 110-120% of GDP[10].

Financial development influences growth rates of sectors within a country and is found to reduce income inequality

Industries that are more dependent on external finance (the difference between investments and cash generated from operations) grow disproportionately faster in countries with more developed financial sector[11]. For example, in Malaysia, which has high levels of financial development, the Drugs and Pharmaceutical industry (which is relatively heavily dependent on external finance) grows at a 4% higher annual real rate than Tobacco (which is relatively less dependent on external finance). In Chile, which was in the lowest quartile of financial development, drugs grew at a rate of 2.5% lower than Tobacco. Empirical research for Italy[12] shows that local financial development has effects on microeconomic growth: ceteris paribus, a firm located in the most financially developed region grows 6% faster than a firm located in the least financially developed region. In India, expansion of directed credit lending (from 1998-2002) to medium-sized firms (requirement for capital stock is between INR 6.5 to 10 million) shows that this increased availability of credit accelerates their rate of growth of sales, and consequently, profits[13]. Moreover, studies at a sub-district/block level show that certain sectors (say secondary sector like cottage and village industries) in a less developed block[14] can outperform the same sector in a more developed block. Hence it is important to understand the existing linkages between institutionalized credit and growth rate of various sectors. Financial deepening has strongly and significantly contributed to raise the average income of the lower 80% of the population and lower inequality across 70 middle and low income countries[15]. With every 0.1% increase in the level of credit available in an economy, head count poverty ratio reduces by 2.5 - 3% (after controlling for income and inequality differences). The positive impact of financial deepening on reducing poverty holds for within-country studies. Empirical studies show that financial depth has a negative and significant impact on rural poverty (head-count ratio and poverty gap) in India[16]. The poverty-reducing effects of financial deepening are transmitted through two different channels: i) entrepreneurship channel on self-employed in rural areas, and ii) migration from rural to urban areas. Also, a large scale state-led bank branch expansion in rural areas from 1977 to 1990 resulted in significant reduction in rural poverty via increased deposit mobilisation and credit disbursement by banks in rural areas[17]. A 1% increase in the share of credit disbursed by rural branches reduces rural poverty by 1.52%. Similarly, a 1% increase in the share of savings held by rural banks reduces poverty by 2.22%.

There exists an equilibrium level of credit for every country

The idea of equilibrium credit, as proposed by Buncic and Melecky[18] is an important concept because it helps identify both excessive and deficient credit provision in an economy. Identifying excessive credit provision becomes significant, especially in light of the 2008 global financial crisis. In other words, equilibrium credit helps to identify the benchmark against which the credit provision in an economy is judged to be excess or not. For example, countries like the Czech Republic, Bulgaria and Lithuania had credit levels more or less at or below their equilibrium until mid-2006, when credit began to expand more aggressively in all three countries. This expansion in credit came together with an expansion in economic activity, where GDP moved well above its potential in 2006-07 for these three countries. Another interesting piece of research suggests that there exists an optimum level of financial depth for any particular economy at a given point in time. In other words, it is the constrained optimum of financial depth or the share of population that can be commercially served in a sustainable manner, given structural country characteristics, technological constraints, and long-term policy choices[19].

Existence of Disparities in growth at a sub-national level

Research suggests that there exist disparities in economic and social development across the regions and intra-regional disparities among different segments of the society have been the major planks for adopting planning process in India since independence[20]. Apart from massive investments in backward regions, various public policies directed at encouraging private investments in such regions have been pursued during the first three decades of planned development. While efforts to reduce regional disparities were not lacking, achievements were not often commensurate with these efforts[21]. It is found that the spatial pattern of growth shows a large difference in growth rates in large cities and medium sized urban areas[22]. It is also noted that differences in infrastructure and state level policies play a key role in understanding variations in regional incomes and growth rates[23]. In this paper, we contend that depth of financial services, specifically credit, also plays an important role in explaining these regional disparities.

3. Data and Methodology

We begin by analyzing annually reported data on GDDP and Credit Depth (defined as the ratio of Total Bank Credit over GDDP) for 32 districts of Tamil Nadu for the period of 8 years between 2004-05 and 2011-12[9] . We have used data on GDDP (current prices) and annual credit outstanding of scheduled commercial banks for each district, and this is also used for all the analyses carried out for this paper. We define Credit Depth as the ratio between total bank credit and GDDP. A significant limitation of using this data is that we have no way of capturing other formal credit deployed such as through NBFCs, HFCs, and others as well as informal credit and this therefore may not represent fully the nature of credit available for each district or sector. Similarly, there is no way of capturing intra-year credit flows as well as investment flows, equity flows, remittances and other inter-state flows. We are also making two large underlying assumptions, namely that credit is deployed in the same sector and district it is sourced from, and that districts are closed economies. There is no independent methodology to verify if the first assumption holds, and we are aware that the second assumption is a strong limitation of the methodology itself. We found that in 2011-12, the Credit-to-GDP ratio for Tamil Nadu was approximately 72% which grew from 53% recorded in 2004-05. However, this high value of overall credit depth in Tamil Nadu was mostly driven by the very high levels of credit depth in urban areas of Chennai (561%) and Coimbatore (131%). It is also the case that between 2004 and 2012, the share of the state's total credit outstanding has increased for urban areas such as Chennai whereas its contribution to the state's GDP has actually reduced. Conversely, districts such as Thiruvallur and Vellore have had relatively low levels of Credit Depth (15% and 27% respectively in 2011-12). Also, The share of the state's total credit outstanding of Thiruvallur and Vellore has decreased while their contribution to the state's GDP has increased (Annexure 1). Figure 1 below provides a snapshot of the increase in credit depth across the state in the time period.

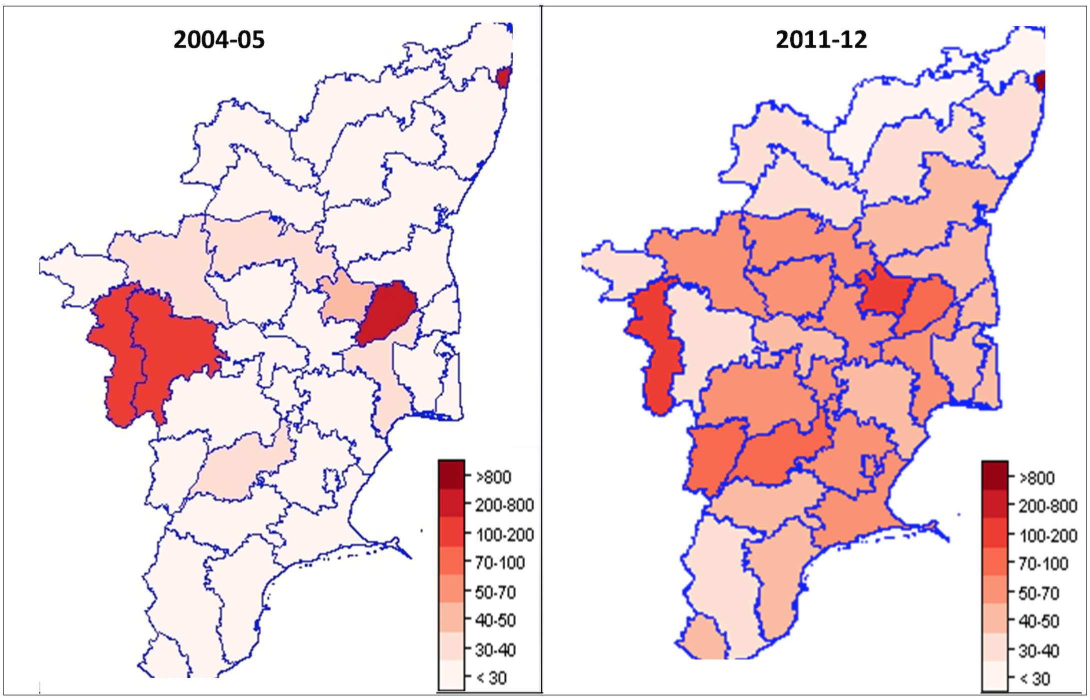

Figure 1: Comparison of Credit Depth levels for districts of Tamil Nadu

Figure 2 is a box plot which captures the variations in credit-to-GDP ratio from 2004-05 to 2011-12. As is evidenced from the plot, the median credit depth (shown by the horizontal line inside the box for each year) in the state is strictly increasing. Simply put, this means that there is a movement towards higher credit depth in the economy of Tamil Nadu from 2004-05 to 2011-12. However, this upward trend could also be primarily caused by the exponential credit growth in urban centers such as Chennai and Coimbatore. Another important observation is that the interquartile range (shown by the length of the box plot) is also increasing from 2004-05 to 2011-12. This could imply that the degree of variation in credit depth between the best-performing district and least-performing district is increasing every year from 2004-05 to 2011-12.

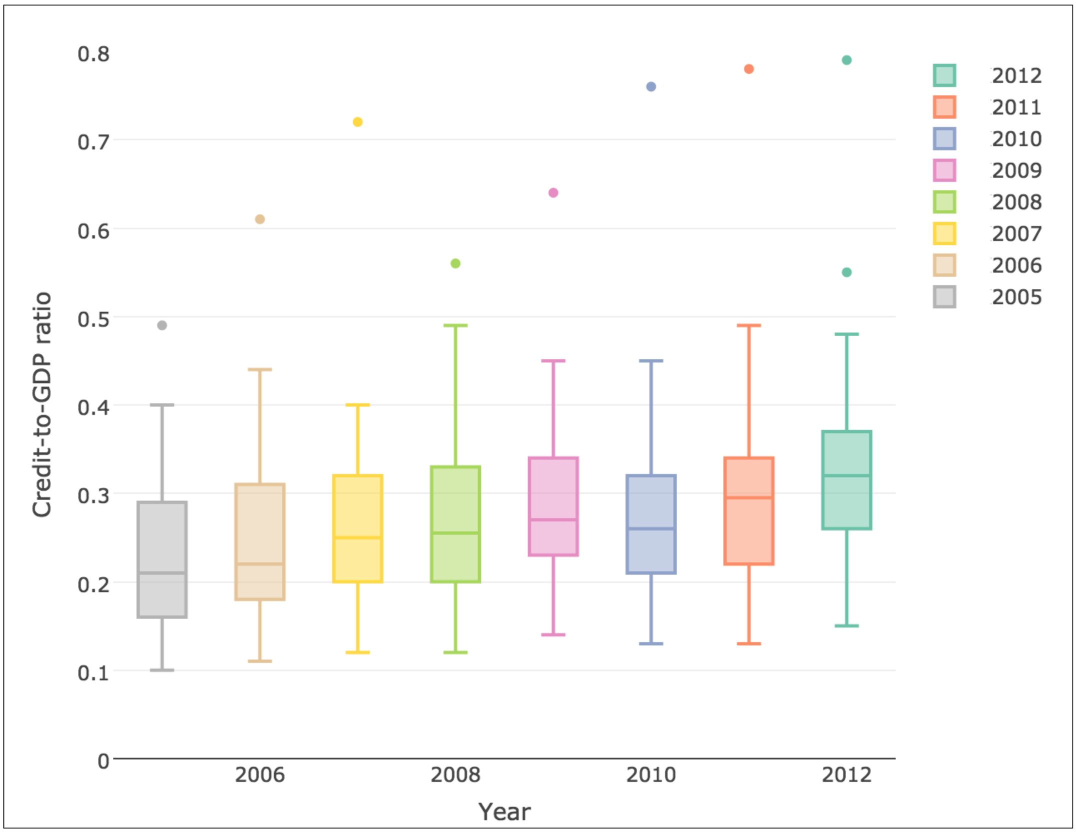

Figure 2: Box plot of District level Credit Depth between 2004-12 in Tamil Nadu

Panel Regressions using a Fixed Effects Estimator

In order to model the relationship between district domestic product with the credit depth, we employ a fixed effects estimator which would help eliminate all the unobserved district specific effects.

$$log(GDDP)_{i,t} = \beta_1 log(CreditDepth_{i,t}) + \beta_k X_{i,t} + u_{i,t} \quad (1)$$

where $X_{(i,t)}$ is a vector of explanatory variables and $u_{(i,t)}$ is error term.

This model accounts only for linear relationship between GDDP and Credit Depth. We contend that there exists a strong relationship between Credit and GDP even in a sub-national economy and that this relationship is non-monotonic. Hence, we account for higher order terms of Credit Depth in (1).

$$log(GDDP)_{i,t} = \sum_{j=1}^{d} \beta_j log(CreditDepth_{i,t})^j + \beta_k X_{i,t} + u_{i,t} \quad (2)$$

We also apply a traditional ARDL approach to account for the possibility of an auto-regression in the model along with lagged effects of explanatory variables. The traditional ARDL process is defined as follows:

$$log(GDDP)_{i,t} = \sum_{k=0}^{m} \sum_{j=1}^{d} \alpha_{k,j} log(CreditDepth_{i,t-k})^j + \beta_k X_{i,t-k} + \sum_{l=1}^{n} \gamma_i GDDP_{i,t-l} + u_{i,t} \quad (3)$$

We estimate these 3 models using fixed effects estimator with clustered standard errors. We also use a robust variance covariance matrix estimator proposed by[24] which assumes a general structure allowing for heteroskadascity and serial correlation of errors. Usually, the optimal lag structure for the ARDL(k,l) model is given by looking at AlC or BIC values of the ARDL model. It is hard to accurately identify different factors that influence GDDP for a panel data exercise. Hence we choose a small selection of explanatory variables such that the model does not have reduced cross-sectional dependence and multi-collinearity. We include explanatory variables to account for infrastructural development (length of surfaced roads per unit sq.km of area), level of rainfall (difference between actual annual rainfall and long term average rainfall), organized sector employment normalized over population (EmploymentPop) of each district and number of micro, small and medium enterprises (MSMEPop) normalised over population. One of the limitations of this analysis is the use of a small of number of explanatory variables used explain District level GDDP effects. We hope to overcome over the next few iterations of this working paper. The summary statistics of variables used in the model are as follows:

Table 1: Summary Statistics

	2004-05			2011-12		
Variables	Mean	Standard Deviation	Coefficient of Variation	Mean	Standard Deviation	Coefficient of Variation
GDP growth rate				0.169	0.0211	0.125
Credit growth rate				0.233	0.048	0.205
Credit Depth	0.357	0.570	1.595	0.532	0.983	1.847
MSMEPop	0.007	0.003	0.441	0.010	0.006	0.594
Length_of_RoadsArea	1.420	0.516	0.364	1.812	0.713	0.393
EmploymentPop	0.033	0.019	0.572	0.033	0.020	0.619
Rainfall	3	1.360	0.454	2.064	0.892	0.432
Share of PSL Credit	0.033	0.060	1.777	0.033	0.0488	1.463

We use the natural log transformation for two particular reasons: we want to estimate the marginal effect of per unit increase in Credit on GDP for each district and this is made easy when applying a log-log transformation to both dependent and independent variables. Also, it is duly noted in literature that log-log transformations may reduce heteroskedasticity and serial correlation especially when dealing with cases where the variance is increasing as the scale of parameters increases. Since our analysis stretches for the period 2004-05 to 2011-12, it is plausible that many of these variables are co-integrated in the long run. Hence we perform stationarity checks on the variables[10] . Although, there are several different factors discussed in literature that may be used to explain the GDDP, district-level panel data on various factors are quite hard to identify. Among the ones we identified, we choose a small selection of explanatory variables that, qualitatively, appeared to be uncorrelated with bank credit and quantitatively, reduced cross-sectional dependence and multicollinearity.

Output Elasticity of Credit Depth

Using the estimates derived from the fixed effects model, we calculate the elasticity (ϵ). We calculate the elasticity by taking the derivative of regression equation with respect to log(CreditDepth)

$$\epsilon = \frac{\partial y}{\partial x} = da_1 x_{d-1} + (d-1)a_2 x^{d-2} + ... + c \tag{4}$$

where a_i are the coefficients of the degrees of $\log(CreditDepth)$ from the regression equation.

This tells us that the elasticity of Credit Depth to GDDP depends on existing credit depth of each district. To find the conditions when $\frac{\partial y}{\partial x} > 0$ and conditions when $\frac{\partial y}{\partial x} < 0$, we plot the equation using β values from the results from model (3).

4. Empirical Results

The models detailed in the equation 1, 2 and 3 are estimated using data detailed in the above section. Table 2 provides the fixed effects panel regression estimates with clustered standard errors:

Table 2: Fixed Effects Panel Regression Estimates

	Dependent variable:				
			log(GDP)		
	Model1	Model2	Model3	Model4	Model5
	(1)	(2)	(3)	(4)	(5)
log(Total_Credit/GDP)	0.907***	0.887***	0.825***	0.668**	0.797***
	(0.145)	(0.089)	(0.266)	(0.276)	(0.191)
I(log(Total_Credit/GDP)ˆ2)			−0.334***	−0.394***	−0.279***
			(0.073)	(0.099)	(0.066)
I(log(Total_Credit/GDP)ˆ3)			−0.134***	−0.138***	−0.111***
			(0.044)	(0.040)	(0.030)
RainfallHigh	−0.064	−0.074	−0.061	−0.075	−0.051
	(0.052)	(0.066)	(0.050)	(0.056)	(0.054)
RainfallLow	0.097**	0.121	0.089	0.125**	0.096
	(0.042)	(0.075)	(0.056)	(0.064)	(0.063)
RainfallNormal	−0.014	0.008	0.0004	0.033	0.018
	(0.048)	(0.063)	(0.052)	(0.052)	(0.054)
RainfallScant	0.013	0.129**	−0.004	0.077*	0.050
	(0.041)	(0.060)	(0.088)	(0.046)	(0.050)
log(EmploymentPop)	−0.762***	−0.750***	−0.663***	−0.654***	−0.710***
	(0.292)	(0.118)	(0.096)	(0.117)	(0.133)
lag(log(EmploymentPop))		−0.142		−0.164	−0.040
		(0.208)		(0.216)	(0.293)
MSMEPop	133.177***	144.089***	146.827***	167.597***	203.560***
	(28.711)	(19.945)	(20.097)	(14.768)	(13.932)
lag(MSMEPop)		21.648**		17.209	45.379
		(9.056)		(17.860)	(35.836)
log(Length_of_RoadsArea)	−0.036	0.044	0.101	0.083	−0.383***
	(0.075)	(0.110)	(0.119)	(0.150)	(0.027)
lag(log(GDP))		−0.163**		−0.163***	−0.192*
		(0.082)		(0.061)	(0.107)
lag(log(Total_Credit/GDP))		0.130		−0.187	−0.117
		(0.116)		(0.244)	(0.348)
lag(I(log(Total_Credit/GDP)ˆ2))				−0.120	0.025
				(0.094)	(0.036)
lag(I(log(Total_Credit/GDP)ˆ3))				−0.004	0.067
				(0.035)	(0.053)
Observations	208	181	208	181	154
R^2	0.637	0.680	0.670	0.721	0.720
Adjusted R^2	0.530	0.533	0.551	0.549	0.519
F Statistic	37.951*** (df = 8; 173)	25.126*** (df = 12; 142)	34.770*** (df = 10; 171)	22.244*** (df = 16; 138)	17.880*** (df = 16; 111)
Note:					*p<0.1; **p<0.05; ***p<0.01

Column 1 estimates the model specification detailed by equation 1 which estimates the relationship between log(GDDP), log(CreditDepth) and the explanatory variables explained in the section above. Column 2 estimates the ARDL specification detailed in equation 3 allowing for a lag structure with a maximum lag length of 1. Columns 3 and 4 provide the estimates for model specifications similar to that of models 1 and 2 respectively with the addition of 2nd and 3rd degree terms of log(CreditDepth) to allow for the non-linear relationship between log(CreditDepth) and log(GDDP). We estimate equation 3 for all d¡=5. However, the results are reported only for d=3 as it represents the best fit. We re-estimate equation 3 with a different lag structure and present the results in column 5. We can infer that the Number of MSME per capita has a significant positive impact on output of the district whereas organized sector employment per capita has significant negative impact. In all the 3 model specifications, we find that the coefficients of degree 3 polynomial of Credit are all significant up to 5%.

Elasticity Estimations

Using the estimates noted in column 5, we calculate the elasticity (ϵ). Substituting d=3 in equation 4, we define the elasticity equation to be:

$$\epsilon = \frac{\partial y}{\partial x} = 3a_1x^2 + 2a_2x + a_3c \qquad (5)$$

where a_1, a_2 and a_3 are the coefficients of $log(CreditDepth)$ of degree 3, 2 and 1 respectively.

Given that a_1, $a_2 < 0$ and $a_3 > 0$, the elasticity equation turns out to be a concave quadratic in log($CreditDepth$) as shown in Figure 3 (left). Transforming equation 5 into a function of CreditDepth, we find that the elasticity curve is represented by Figure 3 (right). The graphs are plotted using out-of-sample estimates derived by using data only from 2004-2011. The coefficients of the model estimated with this sample are provided in column 6. This is done in order to use the Credit Depth values of 2011-2012 to assess the elasticity of the districts. Based on these estimations, we conclude that the districts with credit depth levels between 7% and 250% have a positive elasticity estimate. In other words, 1% increase in Credit Depth would have a subsequent x% increase in output of that district where x>0. Conversely, any district with credit depth levels below 7% or above 250% would experience a subsequent negative impact on growth of output in the district. We also infer that maximum output elasticity of 1.03 is achieved if a district has a credit depth level between 40%-45% (local maxima in Figure 3 correspond to Credit-to-GDP ratio of 43.27%).

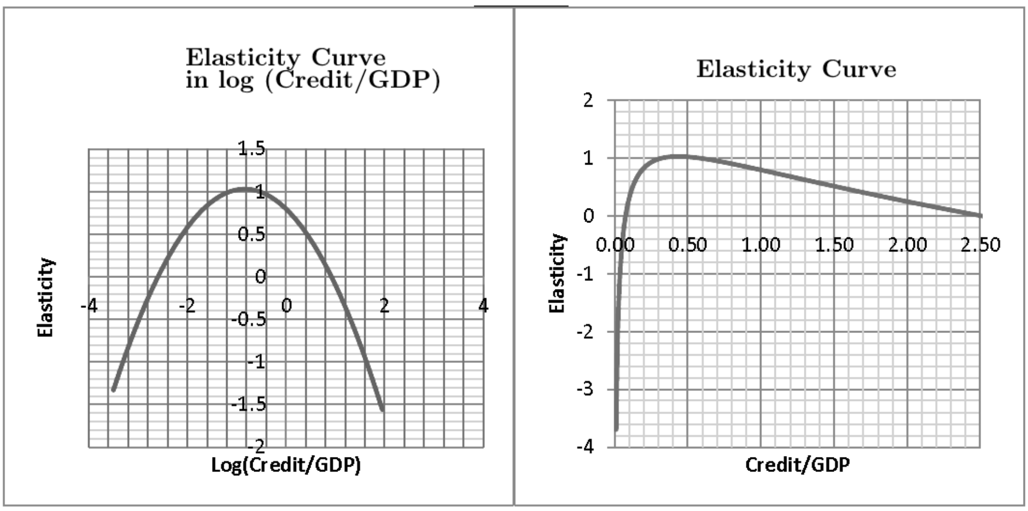

Figure 3: Estimated Elasticity Curves

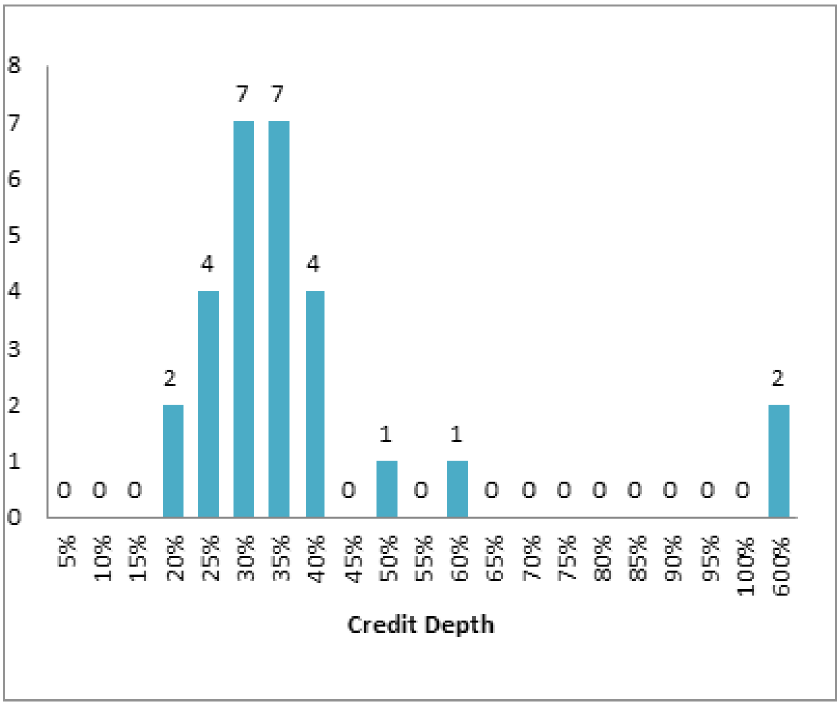

Figure 4: Frequency Distribution of District Level Credit Depth - 2011-12

Figure 4 provides a frequency distribution of the credit depth of districts in the year 2011-12. It shows that there are no districts that have Credit Depth levels between 40%-45%. However, there are 11 districts that have Credit Depth levels between 30%-40%, 13 districts below 30% and 4 districts above 50%. The district with the least credit depth is Thiruvallur with 15% and the district with maximum is Chennai with 560%. Chennai is also the only district with a negative output elasticity of -1.15. In other words, an increase in credit depth of 1% leads to a subsequent decrease of 1.15% in GDDP in Chennai. Given that the districts have negative elasticity due to different reasons, they require different specific actions. For districts in category 1, there needs to be exogenous changes to improve the economic growth of the district and increasing only the credit levels might not be the best solution. Districts that fall under category 2, namely, Chennai (typically urban centers) have excess supply of credit given their GDDP[11] . Figure 5 shows the elasticity estimated for each district along with the change in Credit Depth for districts between 2010-11 and 2011-12. It can be concluded from the above that there is no uniform pattern or relationship between the change in credit depth and the output elasticity of credit estimates. This highlights the fact, given our assumptions hold, that there are some districts (positive elasticity, but weak or no increase in credit depth) where there is very high potential for credit driven growth. As mentioned earlier, typically, a credit allocation process would take into account the demand and supply constraints. Using the elasticity estimates derived using a process similar to the one shown in this paper, it is easy to create a simple design which also takes into account the effectiveness of credit to output. District specific weights w_i can be calculated by solving the optimization problem using the elasticities ϵ_i.

$$\max_{w} \sum_{i} \epsilon_i w_i x_{i,t-1} \tag{6}$$

constrained to

$$D_i <= (w_i + 1) x_{i,t-1} <= S_i$$

where D_i and S_i are district specific supply and demand based constraints that are typically considered. The solution(s) will correspond to an optimal weighting vector for the change in credit (as a factor of GDDP) such that there is maximum increase in GDDP. In this case, demand constraints could refer to predetermined estimates of credit requirements for a particular sector within a district as calculated in PLPs. Supply side constraints could involve any regulatory limits on credit supply and other factors currently being considered in the Annual Credit Plan (ACP)[4] under the Lead Bank Scheme.

One possible solution to the problem is provided in Table 4 (Annexure 2) using a simple uniform weighting vector based on the district level elasticities. This weighting scheme estimates the maximum weight for districts such as Madurai and Thanjavur due to relatively high output elasticity to credit. Based on such weighting scheme, it is assumed that on average, each district (except Chennai) will have increase in GDDP of 1.14%. The only assumption made here is that there is no decrease in credit allocated to any district (for Chennai, credit allocated will remain constant). It is however to be noted that such estimations have to be done on a regular basis as allocations based on such estimations will have a significant feedback effect.

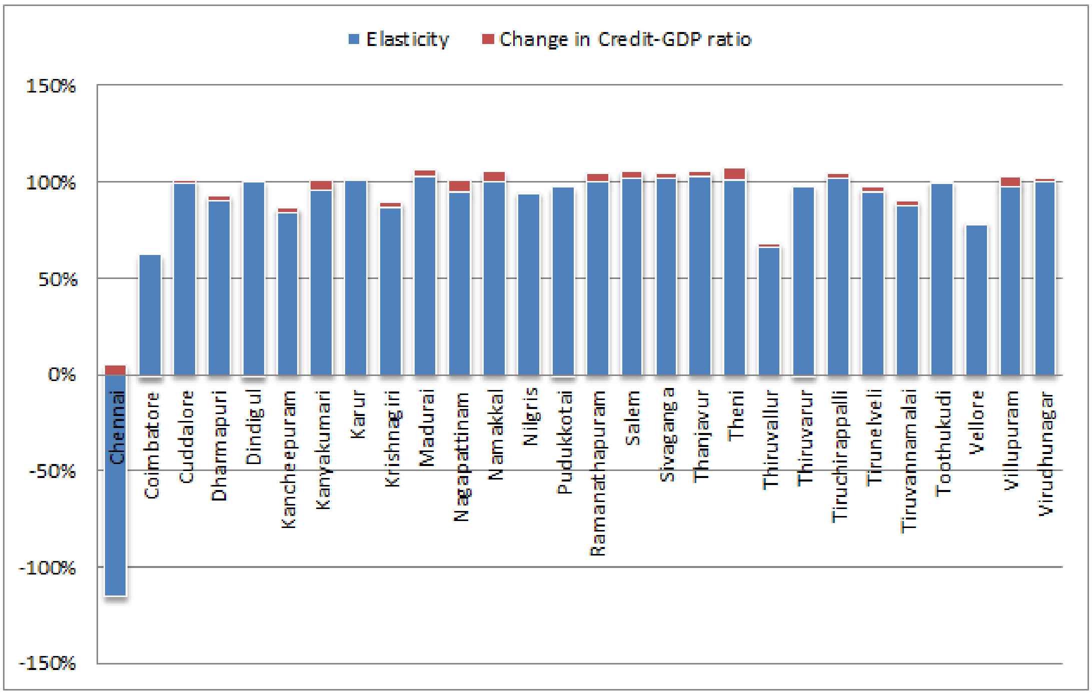

Figure 5: Mapping Elasticities with change in Credit Depth

5. Policy Implications

Based on the analysis shown in the previous sections, we highlight three broad policy implications:

Move towards Elasticity based district-level credit allocations

A fundamental role of the banking and financial sectors is to allocate capital to its most productive use[25]. Traditionally, credit allocations and targets have been driven by demand projections and supply constraints. The Lead Bank Scheme introduced by the Reserve Bank of India in 1969 was aimed at coordinating the activities of banks and other developmental agencies to achieve the objective of enhancing the flow of bank finance to priority sector and other sectors and to promote banks' role in overall development of the rural sector[4]. Under this scheme, a district level credit plan is prepared which takes into account existing demand for credit, availability of infrastructure support, marketing facilities, and policies/programs of Government.

We recommend that the design of allocations under this credit plan must also take into account the potential for growth of output of districts and sectors with a district. A more nuanced credit allocation approach using elasticity based weighting scale to apportion credit to different districts would help direct credit to those productive regions and sectors that are most receptive to credit deployed. In Tamil Nadu, we find that districts could be classified with respect to their elasticity into three categories:

1. *Positively Elastic* ($\epsilon_i >= 1$): Those districts with positive elasticity are considered as districts where credit should ideally be deployed more as they exhibit significant positive impact on the gross output. Deploying additional credit in a district like Thanjavur (with elasticity 1.02%), would likely return a more than equivalent growth in output (A 1.02% increase in GDP corresponding to an increase in credit to the value of 1% of its GDP).
2. *Relatively Inelastic* ($0 <= \epsilon_i < 1$): Those districts which have fractional elasticity. These are districts where credit has a positive impact but only up to a certain degree on the growth of output in a district. These districts should ideally remain close to its existing levels of credit depth but a deeper understanding is required about specific policy actions needed to increase the capacity of credit to have larger impact on growth in these districts.
3. *Negatively Elastic* ($\epsilon_i < 0$): Those districts where increasing the credit levels could have a significant negative impact on output of the district. A district can have negative elasticity for 2 particular reasons:
   (a) *Category 1*: The level of credit depth is too low to have a positive impact on GDDP i.e., below the minimum threshold.
   (b) *Category 2*: The level of credit depth is too high to have a positive impact on GDDP i.e., above the maximum threshold.

Given that the districts have negative elasticity due to different reasons, they require different specific actions. For districts in category 1, there needs to be structural changes to improve the economic growth of the district and increasing credit levels might not be the best solution. Districts that fall under category 2, namely, Chennai (typically urban centers) have excess supply of credit given their GDDP[12]. It is imperative to get a deeper understanding about the potential for credit driven growth in these districts before increasing the level of credit deployed to these districts. Given the enodogenity in credit allocation and the subsequent estimation of growth elasticities and the unobserved exogenous factors that could affect the growth of districts and their credit depth, any proposed elasticity based weighting scheme, as proposed in the previous section, for district and sectoral credit allocations should be revised every year.

Informing the need for non-credit interventions

Different districts have different capacities for credit driven growth. Districts with high output elasticity may benefit from higher allocation of credit. However, in order to achieve homogenous growth of all districts, there needs to be non-credit interventions to improve the capacity for economic growth especially for those districts with low or negative output elasticity and low financial depth. In order to have a holistic view of development and address district and sectoral disparities, we must look at demographic characteristics, social characteristics, developmental and non-developmental revenue expenditures, disbursement of financial assistance for investment, indicators of physical infrastructure development and indicators of financial infrastructure etc. It can be argued that focused investments in social and infrastructural sectors and purposeful de-centralization of targets with accountability would facilitate faster socio-economic development of the backward regions[21]. The analysis shows the importance of the growth of MSME per capita on the growth of district output. This suggests the need for the development of an Ease of Doing Business Index[26] at a district-sector level to identify areas which require targeted investment.

Existing efforts towards homogenous growth could be reinforced by investments in the development and strengthening of several pieces of complementary infrastructure such as rural warehouses, market yards, godowns, silos etc. The Committee for Comprehensive Financial Services for Low Income Households and Small Enterprises recommended that banks should be incentivized to make equity investments to improve complementary infrastructure in low elasticity districts with low credit depth by categorizing these investments eligible for contribution to the overall priority sector lending targets. They should be permitted in sectors where debt already qualifies for PSL but with a multiplier of four, to reflect the higher risk and the illiquid character of these investments. The benefit must accrue as long as the equity investment is held by the Bank with the list of eligible equity investments varied from time-to-time.

Data Collection and Public Access

As mentioned in Section 3, a few limitations of our analysis are because of the unavailability of data such as at a district level. In order to develop such a methodology for district- sector level credit allocations, data collection and disclosure on the following would enhance the quality of estimations:

1. Non-bank formal sources of credit and investments

   Although a majority of funds for non-bank formal institutions are through banks, it is important to capture the credit deployed through non-bank channels which would increase the accuracy of credit depth estimates. It may also explain why credit depth estimates based on just bank credit deployment are high for urban/metropolitan districts.

2. Disbursement and deployment of bank credit

   This paper assumes that there exist closed boundaries between districts. This assumption would not be entirely accurate. It is quite possible that credit originated and hence tagged to a particular district, could be deployed in another district. However, such a limitation could be overcome with better data collection and aggregation.

3. Asset quality and drivers of credit depth at a district-level

   It is assumed that the increase or decrease of credit depth is primarily a function of demand and supply constraints. Hence, it is fundamental to consider factors which influence the supply of credit to different districts and sectors within districts such as the asset quality estimates.

6. Conclusion and Future Steps

This paper is an attempt to a) understand variations and allocations of credit to different sectors and different districts in Tamil Nadu for the time period 2004-05 to 2011-12 and to understand the extent of its effect on GDDP of the respective districts, and to b) devise a methodology for optimal allocation of credit to districts. While it does establish significant variations in credit for districts (with Chennai and Coimbatore leading the rest of the districts in terms of Credit-to-GDP ratio), it also throws light into which districts can be targeted for maximum absorption of credit, and consequent growth in GDP. Given that different sectors and districts have different output elasticities with respect to credit deployed, there is a case to be made for using the elasticities as a tool to guide better allocation of credit to these sectors and districts. This entails that the optimal credit that should be supplied at a sub-national level is a positive measure (objective and fact based) vis-a-vis a normative measure (subjective and value based). This methodology can be further improved upon to consider its application as a tool for sharper assessments of the extent of deficient and excess credit depth, and the quality of inter-regional inter-district as well as inter-sectoral credit allocation by policy-making bodies. Further, the insights from such disparities in credit depth levels can be used to better inform allocations of credit by regional policy-setting bodies such as RBI through priority sector lending, and NABARD through PLPs. The use of high quality data as inputs into the model can significantly strengthen it, especially with respect to better credit data (both in terms of addition of non-bank credit and quality of credit, levels of NPAs and so on), as well as a GDDP data for a longer time period (beyond the 8 years of data used in this paper). For those under-developed districts or sectors exhibiting low elasticities for credit, a deeper exploration by policy-makers on identifying and focusing on non-credit factors, such as literacy, infrastructure levels, healthcare systems, and so on, can possibly have much greater impact on economic development as compared to the deployment of credit, but this to be further studied.

Annexure 1

Table 3: Allied Indicators in 2004-05 and 2011-12

District	Share of Total credit in 2004-05	Share of Total Credit in 2011-12	Share of PSL Credit in 2004-05	Share of PSL Credit in 2011-12	Share of GDP in 2004-05	Share of GDP in 2011-12
Chennai	52.1%	54.5%	31.8%	27.9%	9.1%	7.2%
Coimbatore	14.0%	11.1%	14.6%	8.6%	6.1%	6.2%
Cuddalore	1.2%	1.4%	2.3%	2.9%	3.4%	3.3%
Dharmapuri	0.8%	0.7%	0.9%	1.4%	1.8%	2.2%
Dindigul	1.2%	1.3%	1.7%	2.2%	3.0%	2.8%
Erode	2.9%	2.3%	4.4%	3.5%	4.6%	4.6%
Kancheepuram	1.6%	2.0%	2.7%	3.4%	5.6%	7.1%
Kanyakumari	1.3%	1.5%	2.1%	3.2%	3.4%	4.1%
Karur	0.9%	0.8%	1.7%	1.5%	1.7%	1.7%
Krishnagiri	0.4%	0.9%	1.3%	2.2%	2.3%	3.0%
Madurai	3.1%	2.8%	3.4%	4.6%	4.4%	4.2%
Nagapattinam	0.7%	0.6%	1.7%	1.2%	1.8%	1.6%
Namakkal	1.1%	1.4%	2.0%	2.0%	3.0%	3.1%
Nilgris	0.5%	0.3%	1.0%	0.8%	1.2%	1.0%
Perambalur	0.3%	0.4%	0.8%	0.7%	0.4%	0.4%
Pudukkotai	0.4%	0.7%	1.0%	1.5%	1.8%	1.7%
Ramanathapuram	0.4%	0.6%	0.7%	1.3%	1.6%	1.3%
Salem	2.8%	2.4%	3.3%	3.5%	5.0%	4.8%
Sivaganga	0.5%	0.7%	1.2%	1.8%	1.5%	1.4%
Thanjavur	1.7%	1.3%	2.2%	2.7%	2.9%	2.6%
Theni	0.5%	0.9%	1.4%	2.3%	1.4%	1.2%
Thiruvallur	1.5%	1.4%	1.2%	1.2%	5.8%	6.8%
Thiruvarur	0.4%	0.4%	3.0%	3.8%	1.1%	1.0%
Tiruchirappalli	2.2%	2.2%	2.1%	3.1%	4.3%	4.6%
Tirunelveli	1.8%	1.5%	2.2%	2.6%	4.6%	4.3%
Tiruvannamalai	0.6%	0.7%	0.8%	0.9%	2.3%	2.4%
Toothukudi	1.2%	1.2%	1.9%	1.8%	3.4%	3.0%
Vellore	1.6%	1.4%	2.4%	2.7%	5.7%	5.9%
Villupuram	0.6%	1.1%	1.6%	2.3%	2.9%	2.8%
Virudhunagar	1.7%	1.7%	2.3%	2.6%	4.1%	3.9%

Annexure 2

Table 4: Feasible solution for weight w_i

District	Elasticity	Weight
Chennai	-115.61%	0.00%
Coimbatore	62.06%	2.44%
Thiruvallur	66.27%	2.61%
Vellore	77.60%	3.05%
Kancheepuram	84.45%	3.32%
Krishnagiri	86.78%	3.42%
Tiruvannamalai	87.50%	3.44%
Dharmapuri	90.55%	3.56%
Nilgris	93.59%	3.68%
Tirunelveli	94.74%	3.73%
Nagapattinam	94.80%	3.73%
Kanyakumari	95.97%	3.78%
Pudukkotai	97.22%	3.83%
Villupuram	97.57%	3.84%
Thiruvarur	97.63%	3.84%
Toothukudi	99.11%	3.90%
Cuddalore	99.68%	3.92%
Virudhunagar	100.36%	3.95%
Namakkal	100.46%	3.95%
Ramanathapuram	100.46%	3.95%
Dindigul	100.53%	3.96%
Karur	100.75%	3.97%
Theni	101.04%	3.98%
Tiruchirappalli	101.88%	4.01%
Salem	102.12%	4.02%
Sivaganga	102.36%	4.03%
Thanjavur	102.45%	4.03%
Madurai	102.64%	4.04%

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Notes

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[3]For the purpose of clarity, in this document, financial development is broadly understood as a multidimensional concept that includes measures of depth, access, efficiency and stability. Financial depth refers to the size of financial institutions and markets. Access is the degree to which individuals can and do use financial institutions and markets. Efficiency is understood as the efficiency of financial institutions and markets in providing financial services. Stability refers to the stability of financial institutions and markets as captured through growth volatility.

[4]Estimates from Financial Inclusion Insights (FII) Tracker Survey, March 2016

[5]Estimates from the Domestic Credit to Private Sector (% of GDP), overview per country, World Bank

[6]Estimates from Database on Indian Economy, Reserve Bank of India

[7]As of 2015, the Credit depth for India is at 52.7% and the Agricultural Credit Depth is 36%

[8]Refer[27] for a complete analysis of PSL

[9]In this period, there were 2 new districts namely, Tiruppur and Ariyalur, that were formed which have been carved out of 2 existing districts namely from Erode and Perambalur respectively. For the purposes of robust approximation, we exclude all 4 districts from our analysis and results.

[10]Both log(GDDP) and log(CreditDepth) are found to be stationary variables (I(0)) using augmented Dickey Fuller test for unit roots.

[11]This could be because of the closed boundaries assumption. Credit originated in Chennai could be deployed in other districts to increase their output.

[12]This could be because of the closed boundaries assumption. Credit originated in Chennai could be deployed in other districts to increase their output.