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Abstract

This paper examines the causal relationship between financial liberalization and income inequality using India as a case study. The results indicate that there exists a robust long-run relationship between financial liberalization and income inequality, and their causal relationship is a bi-directional one.

Keywords: Financial liberalization, income inequality

JEL classification: G28; O16; O53

1. Introduction

Underdevelopment of financial systems may intensify income inequality since the poor do not have equal access to credit due to the lack of collateral and connections (Rajan and Zingales, 2003). Reducing credit constraints, which can be achieved through liberalizing the financial systems, helps enable efficient allocation of resources and thereby equalizes distribution of income through allowing the poor to invest adequately in human and physical capital (see, e.g., Banerjee and Newman, 1993; Aghion and Bolton, 1997; Mookherjee and Ray, 2003).

Although the causal relationship between financial development and economic growth has been extensively studied in the literature (see, e.g., Christopoulos and Tsionas, 2004; Rousseau and Vuthipadadorn, 2005; Ang and McKibbin, 2007), so far there is little empirical research exploring the finance-inequality nexus. The importance of this relationship has recently been highlighted by Clarke *et al.* (2006), Beck *et al.* (2007) and Ang (2009a). Their

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results indicate that financial development has a significant effect in reducing income inequality. However, as highlighted in their study, the relationship between finance and income inequality may be driven by reverse causality given that lower income inequality may result in greater political pressures in shaping financial sector policies (Claessens and Perotti, 2007). Therefore, in principle, the relationship between financial liberalization and income inequality may be bi-directional.

This paper aims to enrich the literature by providing fresh evidence on how financial liberalization and income inequality are causally related, drawing on the experience of one of the most rapidly growing developing countries that has also undergone significant financial sector reforms since 1991. We focus on just India instead of a larger set of countries given that the effects of financial liberalization may be heterogeneous across countries at different stages of development.

2. Model, Data and Estimation Techniques

The following empirical specification is adopted to characterize the causal link between income inequality (measured by the Gini coefficient) and financial liberalization (FL_t):

$$Gini_t = f(FL_t,\ control_t) \tag{1}$$

In testing the causal relationship, we first adopt a simple bivariate model and then control for per capita real GDP (ED_t), the share of exports plus imports in GDP (TO_t), the ratio of government consumption to GDP (GOC_t), age dependency ratio (DEP_t) and human capital (HK_t). Age dependency ratio is defined as population ages from 0 to 14 and over 64 as a ratio of working population, with ages from 15 to 64. Human capital is measured by the average years of schooling for population over 25 years old. These control variables enter the specification individually to conserve the degrees of freedom and avoid the problems of multicollinearity.

The construction of the financial liberalization measure follows the approach of Ang (2009a, b). The approach considers nine indicators of financial repressionist policies. Six of them are interest rate controls, including a fixed lending dummy, a minimum lending rate, a maximum lending rate, a fixed deposit dummy, a minimum deposit rate and a maximum deposit rate. These policy controls are translated into dummy variables which take the value of 1 if a control is present and 0 otherwise. The remaining three policies are directed credit programs, the cash reserve ratio and the statutory liquidity ratio. The extent of directed credit programs is measured by the share of directed credit lending in total lending. The other two variables are direct measures expressed in percentages.

Since we want to summarize the financial sector policies to obtain an overall measure of financial liberalization, the method of principal component analysis seems to be a natural choice. The method involves computing the linear combinations of the original variables so that the resulting principal components can capture a large proportion of the variance in the original variables. Specifically, we extract six principal components, which are able to account for 97% of the total variation in the policy variables. These components are then summarized into just one composite measure using eigenvalues as the weights. We have also tried using just one and all principal components. However, our results remain insensitive to the number of principal components extracted due to their high correlation structure. We interpret the inverse of this measure as the extent of financial liberalization (see, e.g., Ang and McKibbin, 2007).

The maximum likelihood approach of Johansen (1988) is adopted as our estimator of the long-run relationship (cointegrating vector). It is based on a vector error-correction (VECM) representation of a VAR model given as follows:

$$\Delta \boldsymbol{X}_t = \boldsymbol{\mu} + \pi \boldsymbol{X}_{t-1} + \lambda \sum_{j=1}^{p-1} \boldsymbol{\gamma}_j \Delta \boldsymbol{X}_{t-j} + \boldsymbol{\varepsilon_t} \tag{2}$$

where $\boldsymbol{X}_t$ is an (n x 1) column of k variables, $\boldsymbol{\mu}$ is an (n x 1) vector of constant terms, p is the lag length and $\boldsymbol{\varepsilon_t} \sim \mathrm{IN}(\mathbf{0}, \mathbf{\Omega})$. The rank of π is equal to the number of cointegrating vectors. The model will be estimated using annual data for India over the period 1951-2004. All variables are measured in natural logarithms.

3. Empirical Results

We now undertake a formal analysis of the dynamic causal relationship between financial liberalization and income inequality in India. First, the integration properties of the underlying variables are examined using two standard unit root tests - the Augmented Dickey-Fuller and Phillips-Perron tests. Our results, which are not reported here to conserve space but available upon request, indicate that all variables appear to be integrated at order one, or $I(1)$, at the 5% level of significance. Given that the variables share common integration properties, we can now proceed to testing for the presence of a long-run cointegrated relationship between the variables.

Table 1: Johansen cointegration tests

	Trace statistic [Maximum eigenvalue statistic]		
	$r=0$	$r \leq 1$	$r \leq 2$
Model A: $(Gini_t, FL_t)$ (sample period: 1951-1990)	17.43* [16.89]*	0.54 [0.54]	
Model B: $(Gini_t, FL_t)$ (sample period: 1951-2004)	22.03** [18.54]**	3.49 [3.49]	
Model C: $(Gini_t, FL_t, ED_t)$ (sample period: 1951-2004)	29.21** [20.08]**	9.13 [6.95]	2.18 [2.18]
Model D: $(Gini_t, FL_t, TO_t)$ (sample period: 1951-2004)	40.21** [26.14]**	14.07 [11.11]	2.96 [2.96]
Model E: $(Gini_t, FL_t, GOC_t)$ (sample period: 1951-2004)	30.83* [21.56]*	9.27 [6.13]	3.14 [3.14]
Model F: $(Gini_t, FL_t, DEP_t)$ (sample period: 1951-2004)	40.63** [28.44]**	12.19 [11.98]	0.20 [0.20]
Model G: $(Gini_t, FL_t, HK_t)$ (sample period: 1951-2004)	33.24* [22.84]*	10.41 [10.31]	0.09 [0.09]

Notes: * and ** indicate 5% and 1% level of significance, respectively.

It is well-known that the Johansen approach may be sensitive to the choice of lag length; we therefore conduct a series of nested likelihood ratio tests on first-differenced VARs to determine the optimal lag length prior to performing cointegration tests. Given the sample size, we have considered a maximum lag length of five. The optimal lag length is found to be one in all models. Thus, we have followed this lag structure in the remaining analyses. Cointegration tests are then performed for the VARs at levels. In Table 1, both the results of Johansen trace and maximum eigenvalue tests unanimously point to the same conclusion that there is only one cointegrating vector at the 1% or 5% level of significance. The results are robust to different sample periods (bivariate systems with pre-liberalization period 1951-1990 and full sample period 1951-2004) as well as alternative specifications (trivariate systems with different control variables).

Table 2: Estimated cointegrating vectors and weak exogeneity tests

Model	Cointegrating vector	Weak Exogeneity tests	
		$H_0: FL \nrightarrow Gini$	$H_0: Gini \nrightarrow FL$
A	$Gini_t = 3.506 + 0.065FL_t,\ \alpha = -0.309$ (3.551) (−2.011) $\chi^2_{SC}(1) = 2.744(0.601); \chi^2_{SC}(2) = 2.481(0.648).$	4.155 [0.041]	9.029 [0.002]
B	$Gini_t = 3.527 + 0.075FL_t,\ \alpha = -0.333$ (3.462) (−2.124) $\chi^2_{SC}(1) = 0.111(0.998); \chi^2_{SC}(2) = 0.435(0.979).$	3.885 [0.049]	7.919 [0.005]
C	$Gini_t = 3.309 + 0.104FL_t - 0.027ED_t,\ \alpha = -0.445$ (4.803) (−0.884) (−2.706) $\chi^2_{SC}(1) = 12.305(0.197); \chi^2_{SC}(2) = 15.669(0.074).$	6.161 [0.013]	9.584 [0.002]
D	$Gini_t = 3.691 + 0.084FL_t + 0.084TO_t,\ \alpha = -0.794$ (5.542) (4.321) (−4.201) $\chi^2_{SC}(1) = 4.172(0.899); \chi^2_{SC}(2) = 6.489(0.691).$	9.915 [0.002]	2.041 [0.153]
E	$Gini_t = 3.812 + 0.136FL_t + 0.106GOC_t,\ \alpha = -0.331$ (3.303) (1.625) (−2.235) $\chi^2_{SC}(1) = 5.161(0.821); \chi^2_{SC}(2) = 6.233(0.716).$	4.551 [0.033]	11.718 [0.001]
F	$Gini_t = 3.558 + 0.167FL_t - 0.083DEP_t,\ \alpha = -0.364$ (5.195) (0.639) (−2.181) $\chi^2_{SC}(1) = 28.881(0.007); \chi^2_{SC}(2) = 11.484(0.244).$	3.261 [0.071]	10.523 [0.001]
G	$Gini_t = 3.473 + 0.104FL_t + 0.379HK_t,\ \alpha = -0.525$ (3.624) (2.232) (−2.919) $\chi^2_{SC}(1) = 15.249(0.084); \chi^2_{SC}(2) = 15.746(0.072).$	7.385 [0.007]	6.462 [0.011]

Notes: figures in round brackets (.) are *t*-statistics and those in square [.] brackets are *p*-values; α is the loading factor; $\chi^2_{SC}(1)$ and $\chi^2_{SC}(2)$ are the Lagrange multiplier test statistics for no first and second serial correlation, respectively.

Following the results of the cointegration tests, we proceed to deriving the long-run estimates. The cointegrating vector is normalized on the Gini coefficient. As we can see from Table 2, all equations perform rather well, although some of the control variables are not statistically significant at the conventional levels. There is also little evidence of serially correlated residuals in the systems. The loading factors (α) that measure the speed of adjustment back to the long-run equilibrium are statistically significant and correctly signed (negative). In particular, the results highlight that the measure of financial liberalization is significantly and positively associated with income inequality. Thus, financial repressionist policies appear to be pro-poor, and financial liberalization is likely to aggravate the income inequality problem in India.

In India, the directed credit programs extended to the agricultural sector and small and medium enterprises over the last few decades have significantly benefited farmers and small traders, allowing the poor direct access to financial services. Reducing the extent of these programs as part of the financial sector reforms is likely to hurt the poor. Similarly, the deregulation of interest rates may increase the costs of lending to the poor since this involves higher transaction costs relative to the size of their loans. These resulting higher lending costs, along with the reduction of direct lending, can have undesirable effect on income inequality since these policies deter the poor from adequately accessing to finance. Furthermore, the closure of a number of banks in rural areas following the liberalization programs has further restricted the poor to access finance.

Cointegration implies the existence of causality, at least in one direction. However, it does not indicate the direction of the causal relationship. Hence, to shed light on the direction of causality, we perform the ECM-based causality tests. Specifically, we use the weak exogeneity test to test the causal relationship. It is a notion of long-run non-causality test based on a likelihood ratio test that follows a χ^2 distribution. The results indicate that financial liberalization has a statistically significant causal impact on the Gini coefficient. Except for the model that uses trade openness as a control variable (i.e., Model D), reverse causality is found in all cases, suggesting that a feedback relationship exists.

4. Conclusions

In this paper, we examined the dynamic relationship between income inequality for India over the period 1951-2004 using a multivariate vector error-correction model. The results show the existence of a robust long-run relationship between the variables, even after controlling for a number of macroeconomic variables. The results further indicate that financial sector reforms do not seem to reduce unequal access to finance, but rather they tend to aggravate income inequality in India.

Notwithstanding the important role of financial market frictions in the theories of poverty and income inequality, researchers so far have not tested the causal relationship between financial liberalization and income inequality. We therefore performed the weak exogeneity tests to shed some light on their causal link. The results suggest a two-way causal relationship between financial liberalization and income inequality, implying that while financial liberalization affects the access to finance by the poor, changes in the distribution of income may also affect the political economy in shaping financial sector policies.

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