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THE RELATIONSHIP BETWEEN FINANCIAL DEVELOPMENT AND INCOME INEQUALITY IN INDIA: EVIDENCE FROM VARX AND ARDL ASSESSMENTS

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ABSTRACT

We examine the relationship between financial development and income inequality in India over the period 1952-2011 using the cointegration techniques of VARX and ARDL. In addressing India's "finance-inequality" nexus, we are concerned with finance's size and efficiency and their linear- and nonlinear effects on income distribution respectively. To consider the influence of India's exposure to globalization, financial crisis, trade and financial openness are taken into estimation. Our findings are: (i) both financial size and efficiency increase inequality; (ii) economic growth increases, whereas other variables increase inequality; and (iii) the nonlinear effect of financial development is not found.

Contribution/ Originality: This study contributes in the existing literature by investigating the relationship between India's financial development and income inequality while we consider that: (i) finance's size and efficiency and their linear- and nonlinear effects on inequality; and (ii) the impacts of financial crisis, trade and financial openness in estimation.

1. INTRODUCTION

It is considered that financial development can contribute to economic growth by promoting capital accumulation and economic efficiency. Thus, as the finance-growth nexus—the topic of whether/how financial depth and economic growth have an influence on each other—has been long debated in the literature, there are a number of empirical findings both from cross-country studies and from time series ones (e.g., (King and Levine, 1993; Demetriades and Hussein, 1996)). Although the debate on the finance-growth nexus has not yet been reconciled, general consensus is that financial deepening is vital for developing economies to achieve and accelerate economic growth.

On the other hand, while there are fewer theoretical and empirical studies as compared with the issue of the finance-growth nexus, the importance of the relationship between financial development and income inequality has been increasingly highlighted by such studies as Claessens and Perotti (2007) and Demirgüç-Kunt and Levine (2009). The basic argument is that finance has implications on income distribution as it can provide different opportunities to different people. One view is that finance is not only pro-growth but also it is a powerful driver of reducing inequality (Banerjee and Newman, 1993; Galor and Zeira, 1993; Mookherjee and Ray, 2003). Deeper finance can make credit cheaper for all investors, in particular small entrepreneurs, boosting entrepreneurial and productive activities, generating employment opportunities and thus enhancing welfare of poor people (Shahbaz and Islam, 2011). Another view is that, since firms and households' availability of financial service and funding are very limited in developing countries, financial development indeed forms the gap between the rich and the poor; more importantly, the gap persists across generations. As finance ends up benefiting the rich who have the collateral or connections to assuage their concerns, there is active discrimination against the poor. As such the economy cannot produce as much as its potential and what it does produce is not distributed fairly (Rajan and Zingales, 2003).

Among several arguments, Greenwood and Jovanovic (1990) argue that financial development is able to improve income distribution, depending on the level of economic development. Thus, the authors put forward the view of a nonlinearity in the finance-inequality relationship—the inverted U-shaped hypothesis—suggesting that income inequality initially rises, then gradually stabilizes and ultimately declines to the extent of financial deepening[1]. Since then, there has been a controversy whether the link between finance and inequality is linear or nonlinear.

The objective of the present study is to investigate the relationship between financial development and income inequality in India. While the effect of finance on inequality has not yet been reconciled theoretically and empirically in the literature, most results are drawn from cross-country and panel data studies that look for a single generalized result by averaging and pooling several countries' data series (e.g., (Clarke *et al.*, 2003; Li and Hu, 2014)). On the other hand, assuming that different countries have different episodes of economic development, relatively few studies are time-series ones that investigate a specific country's finance-inequality causality (e.g., (Law and Tan, 2009; Baligh and Piraee, 2013)). Following the argument that the distributional effect of finance must be heterogeneous across countries at different stages of economic development (Ang, 2010; Bahmani-Oskooee and Zhang, 2015) we conduct a cointegration analysis focusing on India. Specifically, the eradication of poverty has been one of India's major policy issues since it became independent as it is a well-known fact that the country has a chronical inequality rooted to various historical and social reasons. Therefore, it should be important to shed light on India's "finance-inequality nexus"; policy implications drawn from the present study would be useful for researchers and policy makers.

This study contributes to the literature by making the following two inventions. Firstly, financial development is generally proxied by the size of the financial sector's activity since more credit and funding are regarded to directly link to more efficient allocation in an economy. However, while the size-based indexes have been commonly used, it is increasingly questioned whether those proxies are appropriate to reflect the influence of financial depth (Wachtel, 2011). Given the view that financial deepening is a more complicated phenomenon which is not proxied by its volume only, we consider two aspects—size and efficiency—of financial development, supposing that the different indexes might have different effects on income distribution. Secondly, there are a number of economic and institutional factors which might exhibit a substantial impact on the finance-inequality relationship; in examining

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[1]The argument of Greenwood and Jovanovic (1990). can be regarded as a broader perspective of Kuznets (1955). which states that income inequality worsens at the initial stages of economic growth but improves as the growth process continues.

the impact of finance on income distribution, any model should not be misspecified by omitting such essential variables. India initiated trade and financial liberalization—as a part of the broader economic reform—after it was severely hit by a financial crisis in 1991. Since then, India has been recognized as one of emerging economies, achieving high level of economic growth. Based on these experiences, we consider it essential to look at whether/how trade and financial openness and financial crisis influence India's finance-inequality nexus. Trade and financial openness are regarded as powerful tools to achieve higher economic growth by integrating an economy into the goods and financial markets at the global level. On the other hand, deeper finance together with the higher extent of external openness is suspected to make an economy increasingly vulnerable to external shocks and to bring about a crisis. We contend that the distributional impacts of openness and financial crisis might be crucial to address India's finance-inequality linkage in the context of globalizing circumstances.

The present study is structured as follows. Empirical strategy and data are elucidated in Section 2, and methodology is given in Section 3. Empirical findings and policy implications are discussed in Section 4, and conclusion comes in Section 5.

2. EMPIRICAL STRATEGY AND DATA

The empirical strategy for analyzing India's finance-inequality nexus is given by the following basic equations:

$$GINI_t = f_1(FD_t, EG_t, FC_t, TOP_t, FOP_t) \qquad (1)$$

$$GINI_t = f_2(FD_t, FD_t^2, EG_t, FC_t, TOP_t, FOP_t) \qquad (2)$$

Equations 1 postulates that income inequality ($GINI_t$) is Granger-caused by financial development (FD_t), economic growth (EG_t), financial crisis (FC_t), trade openness (TOP_t) and financial openness (FOP_t) respectively. We also introduce equation 2, which has the square term of financial development (FD_t^2), so as to look for the nonlinear effects of finance on inequality.

The underlying variables in the above equations are explained as follows (for the detail, see Appendixes). GINI is the Gini coefficient that is the most common indicator of disparities in income distribution ranging between zero (absolute equality) and one (absolute inequality). In general, although Gini coefficients of all countries are less reliable holding several missing values in each series, India has a relatively good dataset in terms of developing countries[2]. As mentioned earlier, two alternative indicators of financial development (FD) are taken into our study. The first one is the financial size index (FS) that is calculated by credit provided by commercial banks to the private sector (private credit); perhaps, the private credit is the most widely used index of financial depth. Another one is the financial efficiency index (FE) that is computed by the ratio of credit provided by commercial banks to the private sector to total domestic deposit (demand deposit + time deposit); we suppose that, if more credit is allocated—to the private sector but not to the public sector—relative to the volume of total domestic deposit, such a financial system is regarded as more efficient and more competitive (Beck *et al*., 2009). The economic growth index (EG) is proxied by real per capita GDP. The financial crisis index (FC) is produced by computing the volatilities in real exchange rate and the ratio of money supply to foreign exchange reserve respectively and by integrating those two volatilities through the principal component method (Fukuda, 2016). The trade openness index (TOP) is provided by the trade volume (exports + imports) divided by GDP. Based on the idea of Lane and Milesi-Ferretti (2007) who suggested the indexes of external assets and liabilities (net foreign assets) for 145 countries, we make the financial openness index (FOP) by combining the two ratios of exchange reserve to money supply and net foreign assets held by commercial banks to money supply through the principal component method.

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[2] Although researchers have compiled measures of income inequality for many countries over many years, there are measurement problems Deininger and Squire (1996).

The sample period ranges from 1952 to 2011 over which India has a rich experience of economic development. All the underlying variables except FC are converted into logarithm. India's Gini coefficient series are obtained from the latest versions of UNU-WIDER's World Income Inequality Database and the World Bank's Databank[3]. For other variables we use annual data series drawn from IMF's International Financial Statistics (IFS) online database. Table 1 reports the correlations between the underlying variables. The statistics range from 0.002 to 0.899 and show that FS, FE and FC are negatively correlated with GINI, whereas EG, TOP and FOP are positively correlated with GINI. Likewise, as FS and FE are negatively correlated with the coefficient of 0.130, indicating different evolutions of India's financial deepening.

Table-1. Correlations between Underlying Variables

	GINI	FS	FE	EG	FC	TOP	FOP
GINI	1.000						
FS	-0.127	1.000					
FE	-0.404***	-0.130	1.000				
EG	0.005	0.899***	-0.330**	1.000			
FC	-0.174	-0.002	0.046	-0.088	1.000		
TOP	0.293**	0.738***	-0.469***	0.894***	-0.103	1.000	
FOP	0.670***	0.106	-0.553***	0.368***	-0.271**	0.621***	1.000

Note: ***1% level and **5% of significance.

3. METHODOLOGY

The presence of a long-run, steady-state equilibrium in India's finance-inequality nexus is explored in terms of vector autoregressive (VAR) with conditional error-correction models (ECMs). To this end, we use two cointegration techniques: the vector error-correcting autoregressive model with exogenous variables (VARX) of Pesaran *et al.* (2000) and the autoregressive distributed lag (ARDL) bounds test of Pesaran *et al.* (2001). Both the VARX and ARDL models show a definite causal direction through the sign of each underlying variable's coefficient in the cointegrating space; it allows us to identify whether finance and other variables have a positive/negative impact on the Gini coefficient. As its unique advantage, the VARX model can treat some underlying variables as $I(1)$ ("integrated of order 1") exogenous variables that are taken into the cointegrating space but are not treated as endogenous variables. On the other hand, while a strict condition that all underlying variables be $I(1)$ is a requirement in the VARX estimation, the mixture of $I(0)$ and $I(1)$ variables is accepted in the ARDL estimation. These characteristics attribute to the rationale why both the VARX and ARDL techniques are employed to put more robustness in assessing India's finance-inequality nexus.

The estimation starts with unit root tests in order to check the stationarity/integration of the underlying variables. If non-stationary time series do not hold a long-run mean (i.e., their variance is time dependent), the presence of unit root can cause the inaccuracy of the VARX assessment[4]. To confirm whether each variable is either $I(0)$ or $I(1)$, we implement two unit root tests: the GLS augmented Dickey–Fuller (ADF-GLS) test (Elliott *et al.*, 1996)[5] and the Phillips and Perron (PP) test (Phillips and Perron, 1988).

The sequential procedures are separately explained between the VARX and ARDL estimations. On the one hand, for the VARX analysis, the cointegration test of Johansen (1988) is conducted to look for the long-run relationship among the underlying variables. Given that cointegrated variables must have an error correction representation, we present the following VARX error correction model:

[3] Over the sample period 1952-2011, India's Gini coefficient series have some missing values which are supplemented by the missing value analysis procedure.

[4] For the ARDL estimation, we actually need to confirm whether each underlying variable is $I(2)$ or not.

[5] Elliott, Rothenberg and Stock (1996). suggested an efficient test that has modified the Dickey–Fuller test statistics with generalized least squares (GLS) rationale thus dominating the standard Dickey–Fuller test.

$$\begin{bmatrix} \Delta GINI_t \\ \Delta FD_t \\ \Delta EG_t \end{bmatrix} = \alpha_{it} \begin{bmatrix} GINI \\ FD \\ EG \\ FC \\ TOP \\ FOP \end{bmatrix} + \sum_{j=1}^{p-1} \delta_{1j} \Delta GINI_{t-j} + \sum_{j=1}^{p-1} \delta_{2j} \Delta FD_{t-j} + \sum_{j=1}^{p-1} \delta_{3j} \Delta EG_{t-j}$$

$$+ \sum_{j=1}^{p-1} \delta_{4j} \Delta FC_{t-j} + \sum_{j=1}^{p-1} \delta_{5j} \Delta TOP_{t-j} + \sum_{j=1}^{p-1} \delta_{6j} \Delta FOP_{t-j} + inpt + u_{it} \quad (3)$$

where [$\Delta GINI$, ΔFD, ΔFC] is a 3 x 1 vector of the dependent variables, in which we highlight $\Delta GINI$ only[6], [*GINI*, *FD*, *EG*, *FC*, *TOP*, *FOP*] is the cointegrating vector—the error correction term (ECT)—of the endogenous (*GINI*, *FD*, *EG*) and $I(1)$ exogenous variables (*FC*, *TOP*, *FOP*), p is the lag order chosen for the system, and u_{it} is an error terms. To address the inverted U-shaped hypothesis of Greenwood and Jovanovic (1990) the nonlinear effect of financial development on income inequality is estimated with the following 4 x 1 vector VARX specification:

$$\begin{bmatrix} \Delta GINI_t \\ \Delta FD_t \\ \Delta FD^2{}_t \\ \Delta EG_t \end{bmatrix} = \alpha_{it} \begin{bmatrix} GINI \\ FD \\ FD^2 \\ EG \\ FC \\ TOP \\ FOP \end{bmatrix} + \sum_{j=1}^{p-1} \delta_{1j} \Delta GINI_{t-j} + \sum_{j=1}^{p-1} \delta_{2j} \Delta FD_{t-j} + \sum_{j=1}^{p-1} \delta_{3j} \Delta FD^2{}_{t-j} \sum_{j=1}^{p-1} \delta_{4j} \Delta EG_{t-j}$$

$$+ \sum_{j=1}^{p-1} \delta_{5j} \Delta FC_{t-j} + \sum_{j=1}^{p-1} \delta_{6j} \Delta TOP_{t-j} + \sum_{j=1}^{p-1} \delta_{7j} \Delta FOP_{t-j} + inpt + u_{it} \quad (4)$$

where FD^2 is the square term of the financial development indicator that is the proxy for the nonlinear effect. In Equation 4, if the coefficient of FD > 0 and that of FD^2 < 0 in the cointegrating vector, the inverted U-shaped hypothesis is confirmed; but if the coefficient of FD < 0 and that of FD^2 > 0 in the cointegrating vector, we find the U-shaped relationship. For other cases, we conclude that the nonlinearity is not found out for India's finance-inequality nexus. On the other hand, the ARDL framework is given by the following error correction models:

$$\Delta GINI_t = \alpha_{it} \begin{bmatrix} GINI \\ FD \\ EG \\ FC \\ TOP \\ FOP \end{bmatrix} + \sum_{j=1}^{p-1} \theta_{1j} \Delta FD_{t-j} + \sum_{j=1}^{p-1} \theta_{2j} \Delta EG_{t-j}$$

$$+ \sum_{j=1}^{p-1} \theta_{3j} \Delta FC_{t-j} + \sum_{j=1}^{p-1} \theta_{4j} \Delta TOP_{t-j} + \sum_{j=1}^{p-1} \theta_{5j} \Delta FOP_{t-j} + inpt + u_{it} \quad (5)$$

$$\Delta GINI_t = \alpha_{it} \begin{bmatrix} GINI \\ FD \\ FD^2 \\ EG \\ FC \\ TOP \\ FOP \end{bmatrix} + \sum_{j=1}^{p-1} \theta_{1j} \Delta FD_{t-j} \sum_{j=1}^{p-1} \theta_{2j} \Delta FD^2{}_{t-j} + \sum_{j=1}^{p-1} \theta_{3j} \Delta EG_{t-j}$$

$$+ \sum_{j=1}^{p-1} \theta_{4j} \Delta FC_{t-j} + \sum_{j=1}^{p-1} \theta_{5j} \Delta TOP_{t-j} + \sum_{j=1}^{p-1} \theta_{6j} \Delta FOP_{t-j} + inpt + u_{it} \quad (6)$$

[6] Although there are good reasons for believing that income distribution Granger-causes financial development and economic growth, we do not examine those causalities in this study.

where the linier and nonlinear effects of finance on inequality are estimated by equations 5 and 6 respectively. At the first stage of the ARDL estimation, the bounds test, which is based on F-statistics, is performed to check the existence of a long-run cointegrating relationships between the underlying variables, irrespective of whether those variables are $I(0)$ or $I(1)$ (Pesaran and Pesaran, 2009)[7]. When F-statistics exceed greater upper bound critical values, the null hypothesis is rejected and it is judged that there exists a cointegrating relationship between the underlying variables. On the other hand, as F-statistics fall within lower and upper bound critical values, the result is inclusive so that we refer to the results of unit root tests. At the second stage, the optimal lag order of each variable is set either by the Akaike information criterion (AIC) or by the Schwarz Bayesian criterion (SBC). The nonlinear effect of financial development is confirmed—with the same manner we perform in the VARX estimation—through Equation 6.

Following Johansen *et al.* (2000) and Pesaran and Pesaran (2009) who propose techniques taking the element of structural break—in the form of level shift dummy—into the cointegration analysis, we take the structural break dummy (SBD) into the VARX and ARDL estimations. The main purpose of comprising the dummy is to seek a single cointegration ($r = 1$) and to avoid serial correlation in estimation. To this end, break dates in India's EG (real per capita GDP) series are computed by the break test of Lee and Strazicich (2003;2004). The results are given in Table 2[8].

Table-2. Break Dates in India's EG series

Model	Break date(s)
A (one break)	1978
AA (two breaks)	1966, 1978
C (one break)	1991
CC (two breaks)	1972, 1995

Note: Models A and AA = the clash models (break(s) only in the intercept); Models C and CC = the trend break models (break(s) in both the intercept and trend)

To give interference to India's finance-inequality nexus, both the weak and strong exogeneity tests are implemented on the basis of chi-square (X^2) statistics from the Wald test. In conducting the weak exogeneity test, we address the null of H_0: $\alpha_i = 0$; this test looks for the evidence of long-run causality or the significance of the ECT coefficient. The strong exogeneity test examines the nulls of H_0: all δ_{ij}'s $= \alpha_j = 0$ for the VARX estimation and H_0: all θ_{ij}'s $= \alpha_j = 0$ for the ARDL estimation respectively. Thus, the overall causality in the system is identified by the strong exogeneity test, irrespective of time spans (Charemza and Deadman, 1997).

4. EMPIRICAL RESULTS

4.1. Initial Procedures

The estimation of India's finance-inequality nexus starts with the ADF-GLS and PP unit root tests to check the integration properties of the underlying variables. According to the results of Table 3, the variables of GINI, EG, FS, FE, TOP and FOP are detected as non-stationary in their levels but become stationary after taking their first-differences (i.e., $I(1)$) at the 5% level or better. As far as FC is concerned, although the ADF-GLS test result of intercept and trend only—among four categories of the statistics—shows that FC is $I(1)$ at the 10% level, we consider all the underlying variables as adequate since the cointegration analysis is implemented with the use of both VARX and ARDL techniques in this study.

[7] Indeed it is assumed that all the underlying variables are not $I(2)$ in the ARDL estimation, so that there is need to conduct the unit roots tests.

[8] The Lee and Strazicich test is a Lagrange multiplier unit root test that endogenously pinpoints at most two breaks in each series. This test suggests six models. Among them, models B and BB of 'changing growth', which assume break(s) in a trend only, are omitted as most economic time series are described by four models of A, AA, C and CC Lee and Strazicich (2003;2004).

Table-3. ADF and PP Test Results (k = 2, 2000 replications)

	ADF Test		PP Test	
	Inpt.	Inpt. & trend	Inpt.	Inpt. & trend
GINI	-1.465	-1.875	-2.821	-2.654
ΔGINI	-4.493***	-5.238***	-8.492***	-8.542***
EG	2.851***	-0.020	4.632***	1.972
ΔEG	-2.229**	-4.087***	-6.639***	-7.962***
FS	.7802	-1.860	-0.672	-1.788
ΔFS	-2.545**	-3.465**	-9.067***	-9.022***
FS^2	.2947	-1.640	-1.784	-1.574
ΔFS^2	-2.704**	-3.735***	-9.743***	-10.254***
FE	-1.625	-1.899	-1.802	-1.939
ΔFE	-2.663**	-3.993***	-6.179***	-6.151***
FE^2	-1.806	-1.927	-1.978	-2.040
ΔFE^2	-2.374**	-3.802***	-6.504***	-6.455***
FC	-3.301***	-3.476**	-5.357***	-5.312***
ΔFC	-6.036***	-6.047***	-11.373***	-11.275***
TOP	.08535	-0.631	0.488	-2.297
ΔTOP	-2.955***	-4.390***	-9.139***	-9.957***
FOP	-1.099	-1.394	-2.400	-2.788
ΔFOP	-2.664**	-3.743***	-3.831***	-4.079**

Note: ***1% level and **5% of significance. The significance levels are based on critical values simulated with 2000 replications

Next, for the VARX estimation, the Johansen cointegration test is performed at the lag order of two (k = 2) while FC, TOP and FOP are treated as $I(1)$ exogenous variables in the cointegrating vector. The results are provided in Table 4 where the combinations of deterministic components reported in the third column are confirmed as optimal in looking for a single cointegration and no autocorrelation in estimation[9]. The trace statistics show that there is a single cointegration relationship (r = 1) in each of linear and nonlinear VARX models.

Table-4. Johansen Cointegration Test Results (Trace Statistics, k = 2)

VARX linear models				
Model A				
Dep. & end. variables	**$I(1)$ exo. variables**	**Det. components**	**Null**	**Statistic**
GINI, FS, EG	FC, TOP, FOP	Intercept (rest.)	$r = 0$	88.777***
		SBONEB (unrest.)	$r < = 1$	41.902
Model B				
Dep. & end. variables	$I(1)$ exo. variables	Det. components	Null	Statistic
GINI, FE, EG	FC, TOP, FOP	Intercept (rest.)	$r = 0$	76.744***
		SBTWOB (unrest.)	$r < = 1$	30.417
VARX nonlinear models				
Model C				
Dep. & end. variables	$I(1)$ exo. variables	Det. components	Null	Statistic
GINI, FS, FS^2, EG	FC, TOP, FOP	Intercept (rest.)	r = 0	123.579***
		SBTWOB (unrest.)	r < = 1	68.853
Model D				
Dep. & end. variables	$I(1)$ exo. variables	Det. components	Null	Statistic
GINI, FE, FE^2, EG	FC, TOP, FOP	Intercept (rest.)	r = 0	118.641***
		SBONEC (unrest.)	r < = 1	61.058

Note: ***1% level of significance. For both models, the dependent variable is GINI. The statistics are based on critical values simulated with 2000 replications.

[9] The lag order should be treated carefully as the Johansen test is highly sensitive to the choice of lag length. However, as the present study is based on annual series, the lag order of two is set to keep the degree of freedom for the VARX estimation.

On the other hand, the bounds test is conducted for the ARDL analysis with the maximum lag order of one (k = 1) treating GINI as the dependent variable. First of all, in conducting the bounds test, we have confirmed that there is no need to comprise the structural break dummy into the ARDL estimation. It is important to set each underlying variable's lag order in each model; the lag orders of Model G are selected by the Akaike criterion (AIC), whereas those of other models are by the Schwarz Bayesian Criterion (SBC). Table 5 reports that a cointegration relationship is discovered for all four ARDL models respectively.

Table-5. ARDL Bounds Test Results (F-statistics, k = 1)

ARDL linear models			
Model E			
Dep. & end. variables	**Selected lag orders**	**Det. components**	**Statistic**
GINI, FS, EG,	(1, 0, 0, 0, 0, 0)	Intercept (rest.)	4.475**
FC, TOP, FOP			
Model F			
Dep. & end. variables	Selected lag orders	Det. components	Statistic
GINI, FE, EG,	(1, 0, 1, 0, 0, 0)	Intercept (rest.)	4.406**
FC, TOP, FOP			
ARDL non-linear models			
Model G			
Dep. & end. variables	Selected lag orders	Det. components	Statistic
GINI, FS, FS^2, EG,	(1, 0, 1, 0, 0, 1, 0)	Intercept (rest.)	4.475**
FC, TOP, FOP			
Model H			
Dep. & end. variables	Selected lag orders	Det. components	Statistic
GINI, FE, FE^2, EG,	(1, 1, 0, 0, 0, 0, 0)	Intercept (rest.)	3.733*
FC, TOP, FOP			

Note: **5% and *10% of significance. The selected lag orders are given as (GINI, FS/FE, EG, FC, TOP, FOP) for linear models and as (GINI, FS/FE, FS^2/FE^2, EG, FC, TOP, FOP) for non-linear models respectively. The lag orders of Model G are given by the Akaike criterion, whereas those of other ARDL models are by the Schwarz Bayesian Criterion

Before discussing our findings, we need to present the results of various diagnostic tests in Table 6. According to the statistics, while some models indicate the evidence of heteroscedasticity, non-normality and functional form problem, all eight models are free from serial correlation. Hence we consider that empirical findings of this study are plausible to draw policy implications for India's finance-inequality nexus.

Table-6. Diagnostic Test Results

(a) VARX models				
Test statistic	**Linear models**		**Nonlinear models**	
	Model A	**Model B**	**Model C**	**Model D**
Serial correlation	0.405 [.528]	0.182 [.671]	0.126 [.725]	0.432 [.515]
Functional form	0.433 [.514]	1.416 [.240]	0.318 [.575]	2.486 [.122]
Normality	2.618 [.270]	1.925 [.382]	10.161 [.006]	0.019 [.990]]
Heteroscedasticity	2.403 [.127]	1.846 [.180]	0.674 [.415]	7.296 [.009]
(b) ARDL models				
Test statistic	Linear models		Nonlinear models	
	Model E	Model F	Model G	Model H
Serial correlation	0.463 [.499]	2.009 [.163]	0.019 [.891]	1.401 [.242]
Functional form	3.098 [.084]	2.081 [.155]	4.079 [.049]	2.873 [.096]
Normality	32.264 [.000]	38.929 [.000]	26.377 [.000]	23.136 [.000]
Heteroscedasticity	0.141 [.709]	0.034 [.854]	0.223 [.638]	0.138 [.712]

Note: The normality test is based on χ^2-statistics. The other three are on F-statistics. The statistics in parentheses are p-values

4.2. Identified Cointegrating Vectors

Identified cointegrating vectors of VARX and ARDL models together with α (ECT coefficient) and weak exogeneity test statistics are reported in Table 7. The ECT coefficient is important to show the speed of adjustment back to the long-run equilibrium whenever there is a deviation from the steady state in the cointegrating system. In this regard, the ECT coefficient needs to have a negative sign. As given in the third and fourth columns of Table 7, all the ECT coefficients of eight models are statistically significant together with negative signs and acceptable sizes.

In the second column, we normalize the coefficient of GINI to one in the cointegrating vector and confirm the direction of each underlying variable with respect to GINI, that is, whether one variable has a positive or negative impact on GINI is checked by the variable's sign in the cointegrating vector. It should be mentioned that the positive sign is to increase, whereas the negative sign is to reduce income inequality. All the models except Model H—the ARDL nonlinear model—indicate that EG is negative, and other variables are positive to GINI. As far as Model H is concerned, EG, FE and FE^2 appear to be negative, and others are positive to income inequality.

Table-7. VARX and ARDL Cointegrating Vectors

VARX linear models			
Model	**Cointegrating vector**	**ECT**	**WE test**
A	$GINI = 0.016FS - 0.075EG + 0.094FC + 0.163TOP + 0.274FOP + 4.254$	-0.388	17.151***
B	$GINI = 0.163FE - 0.145EG + 0.148FC + 0.126TOP + 0.274FOP + 4.479$	-0.469	37.841***
VARX nonlinear models			
Model	Cointegration vector	ECT	WE test
C	$GINI = 0.906FS + 0.247FS^2 - 0.283EG + 0.164FC + 0.098TOP + 0.047FOP + 5.910$	-0.184	8.552***
D	$GINI = 0.319FE + 0.378FE^2 - 0.134EG + 0.064FC + 0.163TOP + 0.190FOP + 4.554$	-0.587	46.343***
ARDL linear models			
Model	Cointegration vector	ECT	WE test
E	$GINI = 0.044FS - 0.114EG + 0.047FC + 0.029TOP + 0.258FOP + 4.166$	-0.440	17.241***
F	$GINI = 0.029FE - 0.089EG + 0.026FC + 0.072TOP + 0.214FOP + 4.066$	-0.442	17.753***
ARDL nonlinear models			
Model	Cointegration vector	ECT	WE test
G	$GINI = 0.182FS + 0.034FS^2 - 0.125EG + 0.053FC + 0.047TOP + 0.179FOP + 4.401$	-0.478	15.761***
H	$GINI = -0.570FE - 0.942FE^2 - 0.078EG + 0.006FC + 0.045TOP + 0.208FOP + 3.378$	-0.529	19.676***

Note: ***1% level of significance.

4.3. Causality Test Results

The strong exogeneity test is conducted for the total of eight models to give interference to the relationship between financial development and income inequality in India. As we are concerned with the nonlinearity in India's finance-inequality nexus, the results of linear- and nonlinear models are separately discussed[10].

[10] Although the relationship between financial development and income inequality may be driven by reverse causality (i.e., inequality→finance), we focus on assessing the causality of finance→inequality in this study. Nonetheless, there are good reasons for believing that income distribution shapes public policies, including financial sector policies Demirgüç-Kunt and Levine (2009).

4.3.1. Linear Models

Tables 8 and 9 show the causality test results of VARX and ARDL linear models where we control FS/FE, FC, TOP and FOP for GINI. According to Table 8, all weak exogeneity test statistics are significant at the 1% level, so that a long-run adjusting mechanism is observed in all linear models. Likewise, all strong exogeneity test results, with which we look at the overall causality (short-run + long-run) between the underlying variables, are also significant at the 1% level. Referring to the sign of each underlying variable in the cointegrating vector (see Table 7), we provide the causal directions in the fourth column of Tables 8 and 9. It is identified that economic growth (EG) has a favourable effect reducing income inequality; higher growth is important to make an economy more egalitarian. On the other hand, financial size and efficiency (FS and FE), financial crisis (FC), trade and financial openness (TOP and FOP) are associated with higher income inequality. Specifically, since both financial size and efficiency—two alternative indicators of financial development—have their negative distributional effects, we can mention that India's financial sector was not developed to exhibit an inequality-reducing effect over the sample period 1952-2011.

Table-8. Causality Test Results (VARX Linear Models)

***H₀*:FS/EG/FC/TOP/FOP does not cause GINI.**				
Model	**Regressors**	**Weak/Strong Exogeneity**	**Direction**	**Result**
A	ECT(-1)	CHSQ(1) = 17.151***	—	—
	ΔFS & ECT(-1)	CHSQ(2) = 20.096***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 17.726***	Negative	Yes
	ΔFCs & ECT(-1)	CHSQ(3) = 20.142***	Positive	Yes
	ΔTOPs & ECT(-1)	CHSQ(3) = 21.031***	Positive	Yes
	ΔFOPs & ECT(-1)	CHSQ(3) = 24.704***	Positive	No
H₀:FE/EG/FC/TOP/FOP does not cause GINI.				
Model	Regressors	Weak/Strong Exogeneity	Direction	Result
B	ECT(-1)	CHSQ(1) = 37.841***	—	—
	ΔFE & ECT(-1)	CHSQ(2) = 37.890***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 38.255***	Negative	Yes
	ΔFCs & ECT(-1)	CHSQ(3) = 40.271***	Positive	Yes
	ΔTOPs & ECT(-1)	CHSQ(3) = 43.644***	Positive	Yes
	ΔFOPs & ECT(-1)	CHSQ(3) = 47.551***	Positive	Yes

Note: ***1% level of significance.

Table-9. Causality Test Results (ARDL Linear Models)

(b) ARDL linear models				
***H₀*:FS/EG/FC/TOP/FOP does not cause GINI.**				
Model	Regressors	Weak/Strong Exogeneity	Direction	Result
E	ECT(-1)	CHSQ(1) = 17.241***	—	—
	ΔFS & ECT(-1)	CHSQ(2) = 18.215***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 17.355***	Negative	Yes
	ΔFC & ECT(-1)	CHSQ(2) = 23.940***	Positive	Yes
	ΔTOP & ECT(-1)	CHSQ(2) = 19.279***	Positive	Yes
	ΔFOP & ECT(-1)	CHSQ(2) = 22.028***	Positive	Yes
H₀:FE/EG/FC/TOP/FOP does not cause GINI.				
Model	Regressors	Weak/Strong Exogeneity	Direction	Result
F	ECT(-1)	CHSQ(1) = 17.753***	—	—
	ΔFE & ECT(-1)	CHSQ(2) = 20.291***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 18.334***	Negative	Yes
	ΔFC & ECT(-1)	CHSQ(2) = 21.960***	Positive	Yes
	ΔTOP & ECT(-1)	CHSQ(2) = 18.242***	Positive	Yes
	ΔFOP & ECT(-1)	CHSQ(2) = 21.705***	Positive	Yes

Note: ***1% level of significance.

4.3.2. Nonlinear Models

In estimating the VARX and ARDL nonlinear models, FS/FE, FS^2/FE^2, EG, FC, TOP and FOP are controlled for GINI. Since all statistics of the weak exogeneity test are significant at the 1% level in Tables 10 and 11, a long-run adjusting mechanism is found in all nonlinear models. Besides, all strong exogeneity test results are significant at the 5% level or better. Importantly, we look for whether the nonlinearity of each financial development indicator exists or not. In Models C, D and G, both FS/FE and FS^2/FE^2 exhibit a positive sign (FD > 0 and $FD^2 > 0$/FE > 0 and $FE^2 > 0$). On the other hand, in Model H, both FE and FE^2 possess a negative sign (FE < 0 and $FE^2 < 0$) (see Table 7). Thus, neither the inverted U-shaped nor the U-shaped effect is detected in our study of India's finance-inequality nexus; irrespective of square terms or not, each financial index maintains its causal direction over the sample period 1952-2011. As far as the effects of other underlying variables are concerned, economic growth is negative, whereas financial crisis, trade and financial openness are positive to income inequality. Hence the causal directions of the underlying variables are the same as those discovered in the linear analysis.

Table-10. Causality Test Results (VARX Nonlinear Models)

***H_0*:FS/FS²/EG/FC/TOP/FOP does not cause GINI.**				
Model	**Regressors**	**Weak/Strong Exogeneity**	**Direction**	**Result**
C	ECT(-1)	CHSQ(1) = 8.552***	—	—
	ΔFS & ECT(-1)	CHSQ(2) = 8.791**	Positive	Yes
	ΔFS² & ECT(-1)	CHSQ(2) = 9.897***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 9.014**	Negative	Yes
	ΔFCs & ECT(-1)	CHSQ(3) = 11.274***	Positive	Yes
	ΔTOPs & ECT(-1)	CHSQ(3) = 11.767***	Positive	Yes
	ΔFOPs & ECT(-1)	CHSQ(3) = 15.298***	Positive	Yes
H_0:FE/FE²/EG/FC/TOP/FOP does not cause GINI.				
Model	Regressors	Weak/Strong Exogeneity	Direction	Result
D	ECT(-1)	CHSQ(1) = 46.343***	—	—
	ΔFE & ECT(-1)	CHSQ(2) = 60.286***	Negative	Yes
	ΔFE² & ECT(-1)	CHSQ(2) = 60.258***	Negative	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 50.908***	Negative	Yes
	ΔFCs & ECT(-1)	CHSQ(3) = 50.701***	Positive	Yes
	ΔTOPs & ECT(-1)	CHSQ(3) = 52.074***	Positive	Yes
	ΔFOPs & ECT(-1)	CHSQ(3) = 59.501***	Positive	Yes

Note: ***1% and **5% level of significance

Table-11. Causality Test Results (ARDL Nonlinear Models)

***H_0*:FS/FS²/EG/FC/TOP/FOP does not cause GINI.**				
Model	**Regressors**	**Weak/Strong Exogeneity**	**Direction**	**Result**
G	ECT(-1)	CHSQ(1) = 15.761***	—	—
	ΔFS & ECT(-1)	CHSQ(2) = 16.492***	Positive	Yes
	ΔFS² & ECT(-1)	CHSQ(2) = 22.629***	Positive	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 16.673***	Negative	Yes
	ΔFC & ECT(-1)	CHSQ(2) = 25.7169***	Positive	Yes
	ΔTOP & ECT(-1)	CHSQ(2) = 21.144***	Positive	Yes
	ΔFOP & ECT(-1)	CHSQ(2) = 19.575***	Positive	Yes
H_0:FE/FE²/EG/FC/TOP/FOP does not cause GINI.				
Model	Regressors	Weak/Strong Exogeneity	Direction	Result
H	ECT(-1)	CHSQ(1) = 19.676***	—	—
	ΔFE & ECT(-1)	CHSQ(2) = 19.701***	Negative	Yes
	ΔFE² & ECT(-1)	CHSQ(2) = 20.341***	Negative	Yes
	ΔEG & ECT(-1)	CHSQ(2) = 19.990***	Negative	Yes
	ΔFC & ECT(-1)	CHSQ(2) = 24.372***	Positive	Yes
	ΔTOP & ECT(-1)	CHSQ(2) = 19.812***	Positive	Yes
	ΔFOP & ECT(-1)	CHSQ(2) = 23.060***	Positive	Yes

Note: ***1% and **5% level of significance

5. CONCLUSION

Using the cointegration techniques of VARX and ARDL, we estimate a total of eight models to investigate the causality between financial development and income inequality in India over the sample period 1952-2011. One important finding—from all models except Model H—is that while we take both financial size and efficiency separately into estimation, the two variables appear to increase the Gini coefficient, that is, the expiation and amelioration of the financial system are significant to exacerbate India's income inequality. This result agrees with Bahmani-Oskooee and Zhang (2015) and Sehrawat and Giri (2015) but does not with Ang (2010) who confirmed the inequality-reducing effect of financial development. Furthermore, with no evidence of the nonlinear effect of financial depth on income distribution, we also discovered that India's financial system is not releasing the distributional effect as Greenwood and Jovanovic (1990) expected. As far as other underlying variables are concerned, economic growth reduces income inequality, whereas financial crisis and both trade and financial openness are unfavourable to the poor.

As one of emerging economies, India is known with its good economic performance over recent years as well as with prolonged and widespread poverty where the poor have been supported by several types of subsidies. In order to promote economic growth and eradicate poverty, policy makers should always mind implementing financial reforms in a gradual and careful manner. As financial development goes on, financial reforms require efficient allocation of financial resources and price corrections; those policies are likely to harm a vast majority of the poor. While such an implication is drawn from seven models of our study, a single model—Model H—shows that the improvement of financial efficiency reduces inequality. Hence, it is better to mention that the relationship between finance and inequality is not an established one.

We argue that financial development is not entirely bad for the poor. Rather, our findings might be temporary, that is, it takes a longer period of adjustment to trickle down the benefits to the poor. Since the hypothesis of Greenwood and Jovanovic (1990) is not confirmed by the present study, India's financial system has not yet reached its maturity in which the inverted U-shaped relationship between finance and inequality is initiated. For future studies, therefore, more time periods together with a sophisticated methodology are necessary to further address India's finance-inequality nexus.

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Appendix-1. Underlying Variables

Underlying Variable	Description
Gini coefficient (GINI)	The Gini coefficient series are obtained from the latest versions of UNU-WIDER's World Income Inequality Database and the World Bank's Databank. There are some missing values which are supplemented by the missing value analysis procedure.
Economic growth (EG)	EG = log [(GDP/GDF)/POP] where GDP is gross domestic product (line 99B), GDF is GDP deflator (line 99bip) and POP is population (line 99Z).
Financial size (FS)	FS = log (PC/GDP) where PC is private credit (line 32D).
Financial efficiency (FE)	FE = log [PC/(DD + TD)] where DD is demand deposits (line 24) and TD is time deposits (line 25).
Financial crisis (FC)	FC = ER + MTF (The elementary variables are merged by the principal component method to make FC. See Appendix 2).
Trade openness (TOP)	TOP = log [(X + I)/GDP] where X is exports (line 70) and I is imports (line 71).
Financial openness (FOP)	FOP = FRTM + FATM + FETM (The elementary variables are merged by the principal component method to make FOP. See Appendix 3)

Note: All the "lines" refer to those of the International Financial Statistics (IFS).

Appendix-2. Elementary Variables of Financial Crisis

Elementary Variable	Description
Exchange rate (ER)	ER = NER × (USGDF/GDF) where NER is nominal exchange rate (line RF) and USGDF is US GDP deflators.
Money supply/foreign exchange reserve (MTF)	MTF = M/FR where M is money supply (line 35L) and FR is foreign exchange reserve (line 1D).

Note: All the "lines" refer to those of the International Financial Statistics (IFS). Each variable is measured as a squared return, that is, $[\log (ER_t/ER_{t-1})]^2$ and $[\log (MTF_t/MTF_{t-1})]^2$ respectively.

Appendix-3. Elementary Variables of Financial Openness

Elementary Variable	Description
Foreign exchange reserve/money supply (FRTM)	FRTM = log (FR/M) where FR is foreign exchange reserve (line 1D) and M is money supply (line 35L).
Commercial banks' net foreign assets/money supply (FATM)	FATM = log (FA/M) where FA is commercial banks' net foreign assets (line 31N).
Financial account plus net errors & omissions/money supply (FETM)	FETM = log (FE/M) where FAE is financial account plus net errors & omissions (lines 78BJD & 78CAD).

Note: All the "lines" refer to those of the International Financial Statistics (IFS).