Establishing finance-growth linkage for India: a financial conditions index (FCI) approach

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Abstract

Purpose – The global financial crisis of 2008 emphasized the need for monetary policy authorities to have a more comprehensive view of the conditions prevailing in the economy before deciding their policy stance. The purpose of this paper is to outline the construction of a financial conditions index (FCI) and investigate the possible co-integrating relationship between the economic growth and FCI.

Design/methodology/approach – The study employs the PCA methodology, with appropriate augmentations to handle the unbalanced panel data-sets and constructs a FCI for India. It tests the growth-predicting power of FCI by applying the auto regressive distributed lags approach to co-integration and verifies if the FCI is co-integrated with real GDP growth. It also discusses construction of a financial development index (FDI) which tracks the financial markets through M3, market capitalization and credit amount to residents.

Findings – The constructed FCI has a quarterly frequency and is available starting 1998q2. The long-run coefficient of FCI while predicting the real GDP growth is significant at 10 percent. The results confirm that a more-broader index FCI outperforms a narrower index FDI in growth prediction.

Research limitations/implications – By showing that FCI is a better growth predictor than FDI, the study establishes the importance of including the foreign exchange markets, bond markets and stock markets while summarizing the conditions in the economy. The authors hope that the FCI would be helpful to the monetary authorities in their policy decisions.

Originality/value – The paper adds to the few existing studies studies dealing with FCI for Indian economy and constructs a more comprehensive index which tracks multiple markets simultaneously. It also fills the gap in literature by evaluating the correlating relationship between FCI and economic growth.

Keywords Economic growth, Financial development, Principal components analysis, Financial conditions index

Paper type Research paper

1. Introduction

1.1 Financial development and economic growth

The relationship between financial development and economic growth has been a topic for a large number of studies, majority of which (e.g. Blackburn and Hung, 1998; Beck and Levine, 2004; Hassan *et al.*, 2011; Sehrawat and Giri, 2015) confirm a positive causal relationship running from financial development to economic growth. Various theoretical paths have been described to explain these results, but the theoretical base for relationship between financial development and economic growth has been a matter of debate among economists since long. In spite of the large number of studies, the variety of their results compels us to assume that the relationship is highly sensitive to the choice of variables and control variables.

A stable financial system is an important requirement for any economy that needs to achieve the objectives of long-term sustained growth and low inflation. Financial instability,

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on the other hand, can adversely affect the growth of economic activity and reduce economic welfare. To tackle growing pressures on the financial system which lead to instability, the authorities should alter the stance of monetary policy so that the instability is averted and prevent malfunctioning of the market. A well-functioning and developed financial sector serves as an important component of a booming economy by providing for a platform to exchange services, mobilize funds etc. Since Goldsmith (1969) and De Gregorio and Guidotti (1995) confirmed a positive relationship between financial development and economic growth, following the "supply-leading" hypothesis, there have been numerous attempts to effectively track financial development using a financial development index (FDI). Gelbard and Leite (1999) contributed to this by building an FDI for sub-Saharan developing countries. They used various monetary aggregates (and their ratios to GDP) like broad money to GDP, central bank domestic credit to GDP, etc., as indicators while constructing the index. Similarly, Johnston and Pazarbasioglu (1995) used the real cost of capital, volume of intermediation[1], etc., to link financial development and financial reform to economic growth. Following a similar approach, we also build an FDI[2] in Section 5.3 using three different variables, namely, broad money (M3), credit to domestic residents and market capitalization, to compare the growth-predictive power of the financial conditions index (FCI). The FDI is then used to compare the efficacy of the newly constructed financial conditions index (FCI) with regards to growth prediction.

1.2 Motivation behind construction of a FCI

Although stress is not directly observable, considerable research has gone into using financial market variables to study stress. However, stress often manifests itself in movement of financial market variables. Stress in one market can be off-set by benign conditions in some other market. Therefore, knowing the state of financial condition in an aggregate sense is not always straightforward. Considerable information gaps like these exist in financial markets which, in the extreme case, leads to the breakdown of the market functioning. Thus, breaking this information asymmetry assumes importance. To overcome this problem, FCIs are constructed, which show the state of financial condition.

Though a FDI provides a linkage from financial reforms to economic growth, it generally proves not enough. In today's globalized world that is driven by unparalleled financial innovation, it has become imperative to consider the effects of foreign exchange markets, bond yields, credit spreads, etc., along with the traditional monetary aggregates while tracking the financial conditions. Keeping this in mind, we include indicators from all the above-mentioned sub-headings in building the FCI to make it garner a more comprehensive view of the prevailing conditions in the economy than what the FDI provides for.

Ideally, the monetary authorities would want to take corrective measures as soon as possible so as to minimize impact on the real economy. Moreover, they would welcome a feedback measure to assess the performance and effectiveness of the applied corrective measures. A FCI attempts to bridge this gap and makes it simpler and easier for the monetary authorities to evaluate the impacts of the recent policy changes so that corrective measures can be employed sooner rather than waiting for the transmission channel to realize at real economic output. A FCI would serve as a summary indicator for the conditions in the financial market. Moreover, the FCI would also be able to predict the future state of economic output. This would help the monetary authorities to gauge the ultimate impact of a policy change and thus take a corrective action if the impact is not in line with the final goals of the policy. Monitoring financial conditions and stability is not an easy task, as the complexity of current financial markets makes it increasingly difficult. It requires understanding of classical and currently evolving financial markets, their inter-relation and their relation with economic activity. Guichard and Turner (2008) note that FCIs have now transformed into a useful source of information and are increasingly being used in prediction models relating to real economic growth of their ability to predict the stance of financial conditions. Hatzius *et al.* (2010) observe that given the uncertainty surrounding the monetary transmission channel, FCIs are being increasingly to assess the impacts of non-traditional monetary measures on real output of the economy. A FCI works towards this and makes it simpler for the concerned authorities to monitor the financial conditions in a standard lag period. The complex interdependency between monetary policy, financial markets and the state of an economy makes monitoring financial markets and assessing their stability difficult using only a few indicators. Traditional macro-econometric models that were used by the monetary authorities were purely based on interest rates. But during an event of disturbed financial conditions (i.e. financial stress), it may not suffice to capture all the interactions between the financial system and the real economy. This provides for an excellent reason for the construction of an index which would capture a large amount of indicators like data regarding supply of loan funds, spreads, volatility, etc., and provide a useful and easy-to-use summary indicator for the authorities to gauge the present financial conditions and to forecast the eventual effect on the real economy and take a corrective change in the stance if needed.

1.3 Objectives of the study

The major objectives and contributions of this study are:

- to construct a quarterly FCI which provides a comprehensive look of the prevailing financial conditions in the economy and can be used in deciding the monetary policy stance;
- to validate if the newly created comprehensive index is indeed a better growth predictor than the FDI, which only focuses on the development of financial markets; and
- to draw implications of the research for stakeholders and policy makers in devising short-term as well as long-term policies for financial development to sustain long-term economic growth in India.

The remainder of this paper is divided into the following sections: In Section 2, we review a few previous efforts on FCIs and other related indexes. Section 3 outlines, in detail, the procedures and methods employed in this paper to construct a FCI for Indian economy and also highlights the augmentations made to existing methods to improve the FCI's effectiveness. Section 4 lists various variables used in the construction of the index and outlines the justifications for its selection through theoretical paths. Section 5 analyses the results of the applied methodology, provides the interpretation of those results and evaluates the newly created index as a growth predictor. The last section summarizes the contributions of the work, discusses the policy implications of the results and explores scope for future research. Appendices, through a brief introduction, provide a necessary insight into the methodology and provide for more results and outputs.

2. Literature survey

Most of the empirical literature since the 1970s approximates financial development by two measures of financial depth – the ratio of private credit to GDP and, to a lesser extent, by stock market capitalization, also as a ratio to GDP. For example, in an influential industry-level study, Rajan and Zingales (1998) use both measures to show that more financial development facilitates economic growth. More recently, Arcand *et al.* (2012) use the credit to GDP ratio to establish that there is a threshold above which financial development no longer has a positive effect on economic growth. On the macroeconomic volatility side, Dabla-Norris and Srivisal (2013) find that financial development, as measured by private credit to GDP from banks and other financial institutions, plays a significant role in dampening the volatility of output, consumption, and investment growth, but only up to a certain point. Most researchers in this field use variations of these two measures to examine the role of the financial system in economic development in the form of FDI.

And, yet, financial development is a multidimensional process. With the passage of time, financial sectors have evolved across the globe and modern financial systems have become multifaceted. For example, while banks are typically the largest and most important, investment banks, insurance companies, mutual funds, pension funds, venture capital firms and many other types of nonbank financial institutions now play substantive roles. Similarly, financial markets have developed in ways that allow individuals and firms to diversify their savings, and firms can now raise money through stocks, bonds and wholesale money markets, by-passing traditional bank lending.

The constellation of such financial institutions and markets facilitates the provision of financial services. Furthermore, an important feature of financial systems is their access and efficiency. Large financial systems are of limited use if they are not accessible to a sufficiently large proportion of the population and firms. Even if financial systems are sizeable and have a broad reach, their contribution to economic development would be limited if they were wasteful and inefficient. The diversity of financial systems across countries implies that one needs to look at multiple indicators to measure financial development in the form of financial conditions index (FCI).

A first step toward the objectives outlined in the Section 1.2 was taken through the construction of a monetary conditions index (MCI). Freedman (1995), in the annual report by the Bank of Canada, provided rationale for introduction of an MCI, which was based on the interest rates and the real exchange rate. Following the pioneering work by the Bank of Canada, the central banks of Turkey, Sweden, Norway and New Zealand started to use their respective MCIs as a device for interpreting the changes in monetary policy (see Freedman, 1994; Kesriyeli and Kocaker, 1999; Hansson and Lindberg, 1994; Dennis, 1997). The interpretation of MCI for these banks stemmed from a thought that the changes in MCI can be interpreted as the loosening or tightening of the financial conditions. They believed that the MCI would capture the pressure put by the monetary policy on the real economy and thus would capture the inflation trend.

A FCI can be understood as a natural extension to the earlier concept of an MCI. The first attempts toward building a FCI included stock prices and housing prices as asset prices while money market spreads were useful in capturing the yield curve's shape and position. Goodhart *et al.* (2006) state that there is a need for a composite index comprising of banking sector profitability as well as probability of a default to effectively monitor for financial crises.

Any index creation involves assigning weight to the different components involved. The initial works related to FCI creation relied on two methods to arrive at the weights. Dudley and Hatzius (2000) and Goodhart and Hofmann (2000) used the structural models, while Mayes and Virén (2001) and Gauthier *et al.* (2003) used the reduced form model equations. Some recent works of Montagnoli and Napolitano (2005) and Swiston (2008) introduced the methods of dynamic factor analysis, use of impulse responses and Kalman filters for weight derivation. These methods allow for the weights to be dynamically updated over the time. More recently, English *et al.* (2005), Sandahl *et al.* (2011) and Angelopoulou *et al.* (2014) used the method of principal components analysis (PCA) for derivation of weights. This method has some added advantages over the traditional methods (discussed in detail in the next section), while Hatzius *et al.* (2010) used a variant of PCA and iterative dynamic factor modeling.

It is clear from the literature that the selection of variables used for construction plays an important role in the effectiveness of the index. The modest start to transformation to FCI using MCI was achieved when Mayes and Virén (2001) and Goodhart and Hofmann (2001) suggested adding the asset prices in construction of MCI. More recently, Guichard and Turner (2008) and Swiston (2008) realized the role of credit availability and used the survey data relating to lending standards. Taking advantage of PCA's ability to derive a few factors from a large number of variables, English *et al.* (2005) estimated and came up with FCIs for the USA, the UK and Germany, where the number of variables used ranged from 35 to 47 variables per country. Hatzius *et al.* (2010) augmented the approach to increase the span of index creation and also included the variables which had not been considered in the approaches before, mostly quantity and survey-based indicators. Brave and Butters (2010) used the PCA approach and modified it by developing a high-frequency index for the USA that incorporated a total of 100 indicators from various sectors and categories like money markets, debt and equity markets and the banking system. They also developed a dynamic factor model framework by extending the PCA approach which was needed for achieving the high frequency and longevity of period of the index.

Although there has been an extensive use of MCIs and FCIs in major western economies, only a few similar indexes have been constructed for the Asian economies. Though their use is not widespread amongst the central banks in Asia, it is indeed a welcome step to see some more indices coming up for this region in the recent years. Deriving from initial motivation for a FCI, Poon *et al.* (2010) came up with an augmented MCI for the ASEAN economies. They derived the weights for various variables used in the construction of the index using a reduced form model of equations estimated using an auto regressive distributed lags (ARDL) procedure. Another FCI for Japan was developed by Shinkai *et al.* (2010). They used the VAR methodology to derive the weights and examine the role of financial linkages in business cycle transmissions.

In the case of Indian economy, efforts toward FCI were made by Kannan *et al.* (2007), who developed a monetary conditions index for India. Their MCI attempts to take both interest rate and exchange rate channels simultaneously into consideration while considering the effect on stance of monetary policy and evolving monetary conditions. Bhattacharya and Ray (2007) developed a measure of the monetary policy stance from the detailed reading of various monetary policy announcements in India from 1973 to 1998. Their constructed measure of monetary policy stance is then linked to output and prices in a three-variable vector auto-regression framework. Samantaraya (2009) outlined the Reserve Bank of India's efforts to adopt a multi-indicator approach in its conduct of monetary policy. The author develops a monetary policy index by synthesizing the extracted signals from the policy documents and quantitative information embedded in key indicators. Recently, Shankar (2014) developed a FCI for India. It takes into account money, bond, stock and foreign exchange markets and has a monthly frequency. Even though their FCI turns out to be fairly correlated with GDP and IIP, the relationship between the constructed FCI and real GDP growth rates is not adequately studied. We aim to fill this gap using our new FCI.

More recently, Gonzales and Bautista (2013) developed FCIs for five financially developed Asian economies, namely, Hong Kong, China, Japan, the Republic of Korea, Malaysia and Singapore. Their FCIs take into account various categories like banking sector, quantities, interest rates and spreads, etc., and employ the strategy and approach similar to Hatzius *et al.* (2010) for the construction of the indexes. As stated earlier, Angelopoulou *et al.* (2014) built a FCI for the Euro area taking into account 24 different indicators from a wide range of prices, quantities, spreads and survey data. We follow a similar approach and use an augmented PCA approach combined with a dynamic factor model to increase the length of the period used for developing the index. The detailed discussion about the method has been made in Section 3.

Gelbard and Leite (1999) introduced an index for measuring financial development and a set of six indices representing key characteristics of the financial system of 38 Sub-Saharan economies. On similar lines, Ang and Warwick (2007) explored a possibility of linking financial and economic development via building an FDI. We build on these works, utilizing a similar methodology to build an FDI to compare its efficacy with our constructed FCI.

3. Methodology

Two of the most important aspects to be considered for any index creation are selection of variables for construction of index and deriving the weights for each variable.

The selection of variables is majorly based on a theoretical basis so that we capture maximum interactions between the selected variables and the real financial conditions. They are selected such that a comprehensive outlook of the markets is achieved through the index with strong theoretical underpinnings. It is almost always accepted in the literature that using more number of variables would lead to maximising the coverage and thus the created index would reflect the existing conditions more effectively. But, in some cases, one might have to forgo a few variables so as to not lose longevity of the time period or lose the high frequency of the index. Section 4 details out the justifications for the selection of the variables used in this study.

We use the method of PCA with augmentations to elongate the period of construction by allowing unbalanced panel data set to derive the weights[3].

3.1 Transformation of variables

The method of PCA is sensitive to the scales of the indicator values used in running the estimation. Therefore, it is imperative to first normalize the variables before using them in such an analysis. Each variable's value for each period is normalized using the following transformation:

$$X_{i,t}^{N} = \left(X_{i,t} - X_{mean}\right)/X_{stdev}, \tag{1}$$

where $X_{i,t}^{N}$ is the normalized value of indicator "*i*" at time "*t*"; $X_{i,t}$ is the raw value of indicator "*i*" at time "*t*"; X_{mean} is the mean (average) of values of indicator "*i*"; and X_{stdev} is the standard deviation of values of indicator "*i*".

Moreover, the indicator values are standardized to make each indicator's variance equal to one. This makes PCA even less sensitive to the varying scales of indicator values.

3.2 Handling unbalanced panel data set

Applying PCA requires the data of all the constituent indicators available for all the time periods for which the index has to be constructed. Generally, for a developing economy like India, many of the required indicators[4] would be not be available for a long period. This would either force the index to be constructed from lesser number of variables or the time period used for the index construction would have to be decreased and the maximum possible period which covers all the variables would have to be considered. Both of these drawbacks prove to be quite limiting and would hinder the overall effectiveness of the index. We use a combination of PCA and a dynamic factor model to allow for the unbalanced panel data. By an "unbalanced panel," we mean that data for not all of the indicators are available for all the periods. It would be inappropriate to use the regular methods used for dealing with missing values in panel (like replacing with historical mean, etc.) here because the indicators are time-series indicators and it would not make much sense to add the same value for all the values missing for continuous quarters. The method is based on work of Cuevas and Quilis (2012), who partially derive the process from previous works of Stock and Watson (2002) and Doz *et al.* (2011), and the iterative procedural framework used is similar to Hatzius *et al.* (2010). The method is an iterative procedure, mentioned as follows:

(1) Use the longitudinal panel data (see Figure 1; see Cuevas and Quilis, 2012) and perform PCA on the static panel of select indicators[5] and construct an index (using the procedure explained in next section).

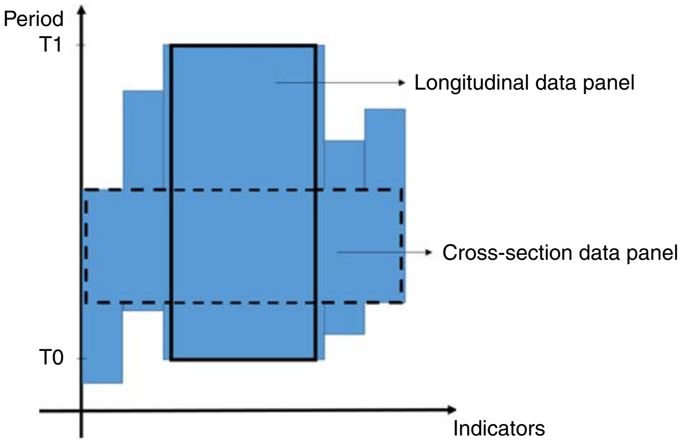

Figure 1.
Longitudinal panel data

(2) Regress each previously excluded indicator with the index constructed in Step 1 and estimate the values for the missing periods.

(3) Using the balanced panel (made up of the known and the now estimated values) of all indicators from time period T0 to T1, perform PCA and create a new index.

(4) Regress each indicator excluded in Step 1 with this new index and recalculate the estimated values for its originally missing periods[6]. Note the differences in the estimated values of each indicator for each missing period.

(5) Steps 2–5 are repeated until a convergence is achieved. The convergence criterion states that the change of the likelihood function should not trespass a given threshold.

(6) Once the convergence is achieved, the final index is created for the balanced panel (with known and final estimated values) using periods from T0 to T1.

The selection of longitudinal panel involves a trade-off between longer period of data and more indicators. This longitudinal panel should be wide enough to include indicators that adequately represent the financial conditions but also should be for a decently long enough period to run a model successfully. We decide to use two to three indicators from under each sub-heading, namely, interest rates and spreads, prices, quantities and bank and other risk indicators. In all, we end up using nine out of total fifteen indicators for the initial longitudinal panel starting from period 1998q2.

3.3 Construction of index

The output of successfully running a PCA results into output of the following tables:

- all components and their corresponding eigenvalues listed in descending order of the variance they explain;
- table of eigenvectors (only shown for "principal" components);
- loading matrix; and
- scoring coefficient matrix.

We use Kaiser–Guttman rule[7] to decide on the number of components to be used as "principal." The scree plot[8] is also a useful visual aid for determining an appropriate number of principal components. In our case, the final PCA that leads to convergence give similar results for the selection of the number of principal components from both the Kaiser rule as well the scree plot.

After deciding on the number of principal components, we generate the eigenvectors. The table with extracted eigenvectors for all the indicators can be seen in Table III. The values in the eigenvector for a component are basically the value of coefficient to be used with the indicator's value in calculating the value of the component. For example, the "i"th component value for a period "t" can be calculated as:

$$PC_t^i = C_{i,1} \times X_{1,t} + C_{i,2} \times X_{2,t} + \ldots + C_{i,n} \times X_{n,t}, \tag{2}$$

where PC_t^i is the "i"th principal component's value at time "t"; $X_{j,t}$ is the value of indicator "j" at time period "t" (transformed); $C_{i,\ k}$ is the coefficient of indicator "k" in extracted eigenvector for component "i"; and n is the number of indicators.

Once the values of principal components for all the time periods are calculated, we proceed to calculate the FCI. For example, if we have "m" number of principal components from the Kaiser–Guttman rule, the final value of FCI at a time "t" is calculated as:

$$FCI_t = c_1 \times PC_t^1 + c \times PC_t^2 + \ldots + c_n \times PC_t^n, \tag{3}$$

where FCI_t is the value of FCI at time "t"; PC_t^i is the principal component "i"s value at time period "t"; c_i is the proportion of variance explained by component "i"; and m is the number of principal components.

The values of FCI for all the periods are then normalized[9] again to bring values of FCI to be reported in terms of number of standard deviations away from the historical mean. These normalized values are then used in further analysis, as stated in the next section.

3.4 Methods for evaluation of FCI

A FCI pools the information from various financial indicators, and, therefore, is representative of a wide range of financial conditions. The next logical step is to confirm if the constructed index performs better in prediction of the future real economic activity than the single indicator variables.

The empirical relationships between the constructed FCI and growth in real GDP[10], modeled with Equation (4), are analyzed using the ARDL method proposed by Pesaran *et al.* (2001).

The ARDL approach is used due to its proven advantages over other co-integration methods in recent times. The unit root integration order requirements for the ARDL method are slightly less limiting than other co-integration methods like Johansen and Juselius (JJ) (Johansen and Juselius, 1990) and Engle and Granger tests (Engle, 1984), as these tests would need both the series to be integrated of the same order 1, i.e. I (1). Otherwise, their results would not be interpretable. On the contrary, the ARDL technique allows for the variables to have any order less than equal one (i.e. either I (1) or I (0)). Moreover, it is not necessary that all the variables have same order of integration:

$$GROW_t = \alpha_0 + \beta_0 \times FCI_t + \varepsilon_t. \tag{4}$$

The ARDL bounds test provides a simpler way for empirical analysis when compared to the multivariate model co-integration techniques in JJ (Johansen and Juselius, 1990). Once the lag order is fixed[11], it allows for simple OLS regression of the co-integrating relationships. The added advantage in ARDL technique is that it would allow for incorporating the short-run dynamics into the error correction model (ECM) (see Equation (7)) without losing any long-run information.

The ARDL procedure involves three major steps:

(1) OLS regression of the unrestricted ECM model (Equation (5));

(2) estimation on a long-run co-integrating relationship established by the bounds test (Equation (6)); and

(3) estimation using the restricted ECM model described in Equation (4) used to investigate the short-run dynamic parameters (Equation 7):

$$\Delta GROW_t = \delta_0 + \delta_1 \times T + \delta_2 \times FCI_{t-1} + \sum_{i=1}^{q} \alpha_i FCI_{t-i} + \varepsilon_t, \tag{5}$$

$$\Delta GROW_t = \delta_0 + \delta_1 \times T + \sum_{i=1}^{q} \delta_i FCI_{t-i} + \varepsilon_t, \tag{6}$$

$$\Delta GROW_t = \mu + \sum_{i=1}^{q} \delta_i \Delta GROW_{t-i} + \sum_{i=1}^{q} \alpha_i FCI_{t-i} + \Theta ECM_{t-1} + \varepsilon_t. \tag{7}$$

ARDL uses an unrestricted/unconstrained error correction model in Equation (5) to estimate the long-run and short-run relationships between the concerned variables (here *GROW* and *FCI*). Here, α's are the short-run coefficients while δs are the long-run coefficients. The null and alternate hypotheses go as:

H_0. $\delta_1 = 0$.

H1. $\delta_1 \neq 0$.

The relationship established for a bound-testing approach for long-run and short-run dynamics is specified through Equation (6). The order of lags (q) is selected using SIC (Schwarz, 1978).

Equation (7) specifies the restricted version of the ECM used to analyze the relationships and short-run co-integration dynamics. Here, the α's are the short-run coefficients to equilibrium, Θ is the speed adjustment coefficient while ECM_{t-i} is the lagged error correction term obtained from the long-run equilibrium relationship.

The next section outlines the data series/indicators used in construction of the index. It tries to provide a linkage that we ideally want to track using the selected variables and also provides for the sources, start and end periods for each selected variables.

4. Data and Selection of variables

It is imperative to select a correct set of variables which would ideally model the financial conditions effectively. But defining "correct" in this context can indeed be tricky. To allow the index to have a quick reaction time, building a larger frequency index is also an objective. Moreover, we would want to incorporate as much historical knowledge as we can. Combining the above goals makes it a three-pronged objective that we would want to maximize the following: frequency of the index, lengths of data series (indicator variables) used and number of indicator variables used in the construction of FCI.

In order to satisfy maximum of the above objectives, we select 15 quarterly data series from 1991q1[12] to 2015q4 as indicator variables in the construction of the FCI. These series fairly model the financial conditions in the Indian economy. Moreover, the data for these indicators are available on a quarterly basis, thus fulfilling the second objective of building a high-frequency index of with a frequency of one value per quarter. The methodology explained in Section 3.3 provides for handling of the unbalanced panel and helps to incorporate a larger number of indicators without losing any period's historical knowledge.

The list of all the indicator variables, their sources, the periods they are available in and the transformations applied to them before further usage in index construction (as described in Section 3.3) are listed in Table I. The selection of indicator variables goes with a general objective of capturing majority of the financial conditions. The data series are categorized in four different sub-headings, namely, interest rates, prices, quantities and banking sector and other risk indicators. This categorization in four different sub-headings mentioned above helps in evaluating the impact of each category on the FCI and the future real economic activity separately:

(1) The column title T indicates the transformation applied to the raw data. 1 means level data used as it is, 2 means logarithms of the data values used and 3 means the first difference of logarithms.

(2) The abbreviations in the sources column are for the following: US Fed – US Federal Reserve Bank; DBIE – Reserve Bank of India's Database on Indian Economy; BSE – Bombay Stock Exchange, BIS – Bank of International Settlements; and AC – authors' calculations.

(3) The data for bank sector β, BSE SENSEX volatility are taken from BSE's website, while the volatility and β is calculated by the authors. Similarly, the data for individual interest rate yields were obtained from various online resources but the spreads were calculated by the authors' own calculations.

(4) The last column shows the abbreviations that are used for the variables/indicators throughout this paper.

(5) First difference of logarithms are calculated Q-o-Q and are calculated as the average value of Q_i minus the average value of Q_{i-1} (Figure 2).

Literature on MCIs and FCIs and the coverage provided by them provides an excellent starting point for the selection of financial indicators to track for the Indian economy. Though many of these had to be dropped as the same/equivalent, data series for Indian

S. No.	Series name	T	Sources	Start	End	Abbr. used
	Interest rates					
1	3 month–3 year bond yield spread	1	AC	2001q1	2016q1	m3 y3spr
2	3 month–10 year bond yield spread	1	AC	2001q1	2016q1	m3_y10spr
3	3 year–10 year bond yield spread	1	AC	2001q1	2016q1	y3_y3spr
4	Sovereign spread (US3M–US10Y)	1	US Fed	1996q1	2016q1	us_t_spr
	Prices					
5	BSE SENSEX	3	BSE	1994q4	2016q1	dlsensex
6	Foreign reserves	3	DBIE	2001q1	2016q1	dlfr
7	Market cap	3	DBIE	1994q3	2016q1	dlmcap
8	Consumer price index	2	DBIE	1998q4	2016q1	dlcpi
	Quantities					
9	M3 (broad money)	3	DBIE	1991q1	2016q1	dlm3
10	Credit to domestic Residents	3	DBIE	1999q1	2016q1	dldr
11	Credit to commercial sector	3	DBIE	1999q1	2016q1	dlcr
	Bank conditions and other risk indicators					
12	Bank sector β	1	AC	1999q1	2016q1	bsb
13	BSE SENSEX volatility	1	BIS	1999q1	2016q1	bse_vol
14	CPI-based REER	2	AC	1994q1	2016q1	reer
15	REER volatility	1	AC	1997q1	2016q1	reer_vol

Note: AC, author's calculation

Table I. Financial indicators

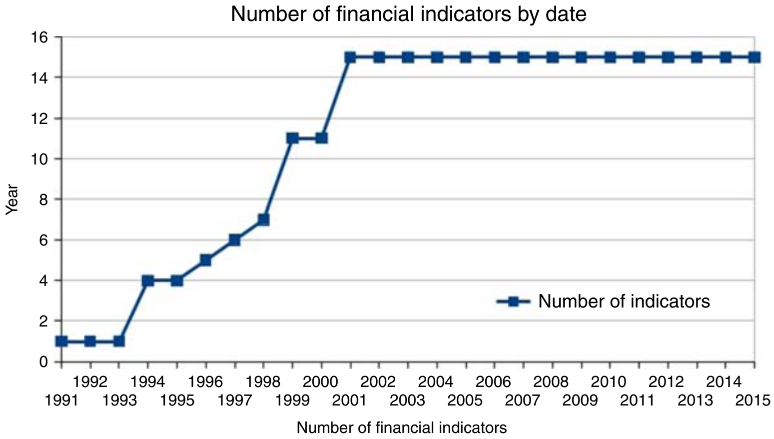

Figure 2.
Number of financial indicators available by year

economy were not directly available or were not available in the required quarterly frequency. Moreover, arriving on a criterion to categorize the indicators into sub-headings helped to ensure the coverage of all the major aspects of financial conditions and helps in finalizing of the 15 series mentioned in Table I. All the series used are brought to same quarterly frequency. Some of the series which are available in more frequent intervals (e.g. BSE SENSEX is available as "daily" closing value) are then averaged over the quarter so as to bring them to the same frequency.

We ensured the selection of various yields and term spreads because they effectively indicate the risk factors in the market scenario[13]. For covering all cases amongst short-term, medium -term and long-term bond yields, we use spreads between three different types of bond instruments[14], namely, three-month bond–ten-year G-Sec yield; three-month bond–three-year bond and three-year bond to ten-year G-Sec yield. The term spreads (the shape of the yield curve) imply the scarcity of short-term liquidity as well as diminished bank profitability when the short-term rate exceeds the long-term rate (i.e. yield inversion). The tracking of the above-mentioned term spreads would enable us to model liquidity risks in such instances. These spreads would ideally reveal market risk perception and risk tolerance. Changes in these spreads should also correspond to changes in prices of other financial products. For example, an increase in these spreads would indicate the overall borrowing costlier for the Government as well as private players[15], thus being an indicator of stress. The data set used likewise includes the international term structure as captured by the US term spread (ten-year treasury note vs three-month treasury bill) which reflects foreign liquidity conditions as well as expectations of growth across the globe.

For including the effect of prices in financial tracking, we include BSE SENSEX[16], Foreign reserves with the RBI (in terms of US$), market capitalization of the listed companies and the consumer price index (CPI). The asset prices would be better tracked through the RBI-released house price index. But since the series is available only for a very short period (from Q4: 2008–2009), we prefer to use the CPI as a proxy for the said index. In hope of including the effects of financial leverage[17] in the economy, we employ market capitalization as a proxy for economy-wide financial leverage (similar to Hatzius *et al.*, 2010). Similarly the quantity-related (stock) indicators are included by inclusion of M3 (broad money), credit to domestic residents and credit to the commercial sector[18]. The inclusion of M3 is based on previously established empirical evidence for direct relationships of M3 with growth and inflation. Moreover, M3 is widely regarded as the economic indicator to assess the amount of liquidity in the economy.

Finally, the banking sector performance related indicators like the bank sector β[19] and other risk indicators like volatility of BSE SENSEX, CPI-based real effective exchange rate (REER) are grouped in a separate sub-heading to ensure coverage of miscellaneous risk factors. Another common indicator for stress in any market is the volatility of the prices in the market. Therefore, we also include the volatility of BSE SENSEX and volatility of CPI-based REER to capture the stress in their respective markets. Measures of asset price returns[20] and volatilities are considered to determine periods of potential financial disruption. Similarly, volatility of BSE SENSEX may indicate possible credit impairment while reflecting market risk and investor uncertainty about fundamental values. Throughout the calculations, the volatility is based on the standard deviation of the series involved.

While including the above-mentioned indicators, we also try to cover the stress conditions in the foreign exchange markets. A deterioration in the CPI-based REER would automatically signal stress in the foreign exchange market. In case of economies with the exchange rate actively managed by the central bank (esp. in stress conditions), the depletion of foreign reserves would also track stress in the foreign exchange market. Increase in FIIs and FDIs would indicate favorable investment climate in the economy and would be adequately reflected in the foreign reserves with the RBI.

The next section describes the results of all the applied procedures (as described in Section 3) and provides for an interpretation of these results.

5. Results and analysis

5.1 Construction of index

We apply the methodology explained in Section 3 on the data series mentioned in the previous section[21]. The final complete balanced data panel[22] consists of indicator values from 1998q2 to 2015q4. Thus, the constructed FCI is available for a period from 1999q2 to 2015q3. The results are presented below in form of various tables and the required figures.

Following tables and figures show the results of applying PCA to the data series with the appropriate transformations applied as shown in Table I.

Table II lists down the eigenvalues of all components and the proportion of variance explained by each of the component. As stated in Section 3.3, we use the Kaiser–Guttman rule (Kaiser, 1957, 1991) to decide the number of components to be considered as principal. Therefore, we limit the principal components to five as the first five components have their eigenvalues above 1.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.289	0.548	0.219	0.219
Comp2	2.741	0.684	0.183	0.402
Comp3	2.057	0.717	0.137	0.539
Comp4	1.340	0.261	0.089	0.629
Comp5	1.079	0.135	0.072	0.701
Comp6	0.944	0.114	0.063	0.763
Comp7	0.830	0.167	0.055	0.819
Comp8	0.664	0.077	0.044	0.863
Comp9	0.587	0.179	0.039	0.902
Comp10	0.408	0.020	0.027	0.929
Comp11	0.388	0.069	0.026	0.955
Comp12	0.319	0.067	0.021	0.976
Comp13	0.251	0.148	0.017	0.993
Comp14	0.103	0.103	0.007	1.000
Comp15	0.000	0.000	0.000	1.000

Notes: Number of obs = 70; number of components = 5; trace = 15; ρ = 0.7005; rotation: (unrotated = principal)

Table II. Principal components/ correlation

Moreover, as a second check, the cumulative variance explained by the final index (FCI) (created by weighted average of the five components) is greater than 70 percent.

Figure 3 shows the screen plot for the eigenvalues generated from the methodology explained in Section 3.3. According to the screen plot, we could have stopped at four components, since the remaining eigenvalues start to fall in a straight line from the fifth eigenvalue. As reported earlier, according to the Kaiser–Guttman rule, we would select five components. Therefore, based on results of both the criteria, we select five components since we would want to maximize the variance explained by the final FCI.

Table III shows the coefficients of the eigenvectors formed by the first five components. It also lists how much of the variance in the particular series has remained unexplained even after considering five components. Table IV is similar to Table III in terms that it shows the loadings of each of the 15 indicator series used in construction of the individual components. In addition, it shows the loading contribution of each series to the final index. The results in weighted loadings are mostly as expected. The weighted loadings of coefficients of credit to

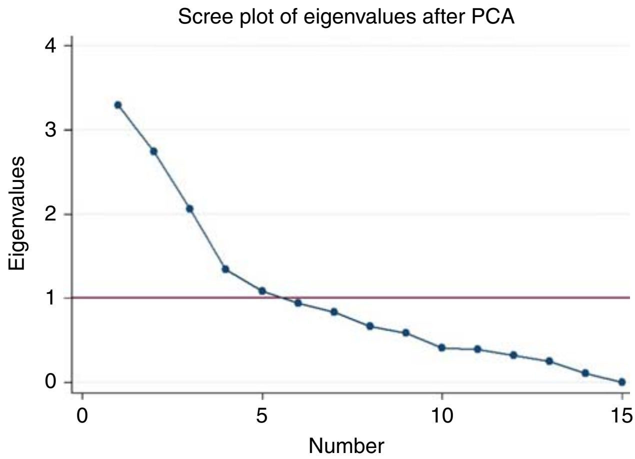

Figure 3.
Scree plot of eigenvectors from PCA

Table III.
Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
dlm3	0.3955	0.1691	0.0488	0.2933	−0.0748	0.281
dlreer	0.0772	−0.3112	−0.1139	0.1447	0.4706	0.4712
reer_vol	−0.2256	0.1053	0.4217	0.1697	0.2732	0.3172
bsb	−0.2361	−0.0937	0.4124	0.3967	−0.2719	0.1519
dlmcap	−0.0386	−0.2341	−0.0775	0.3212	0.4122	0.511
us_t_spr	0.1383	0.1734	−0.2796	0.1775	0.4668	0.4164
dlcr	0.3466	0.1879	0.1377	0.3671	0.0016	0.2885
dldr	0.3789	0.2407	0.333	0.1928	0.0148	0.09078
dlfr	0.1769	−0.1953	−0.3545	0.236	−0.3956	0.2903
m3_y3spr	−0.3464	0.298	−0.1508	0.3285	−0.1134	0.1568
m3_y10spr	−0.355	0.3841	−0.1992	0.2358	−0.0208	0.02458
y3_y10spr	−0.2057	0.3706	−0.1993	−0.0527	0.1671	0.3688
dlsensex	−0.0523	−0.4265	−0.0336	0.2767	−0.0219	0.3869
bse_vol	0.3015	0.2781	0.0676	−0.2664	0.0823	0.3771
dlcpi	−0.1829	−0.0742	0.4349	−0.1753	0.1771	0.4108

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Wtd loading
dlm3	0.396	0.169	0.049	0.293	−0.075	0.207
dlreer	0.077	−0.311	−0.114	0.145	0.471	−0.013
reer_vol	−0.226	0.105	0.422	0.170	0.273	0.089
bsb	−0.236	−0.094	0.412	0.397	−0.272	0.005
dlmcap	−0.039	−0.234	−0.078	0.321	0.412	−0.005
us_t_spr	0.138	0.173	−0.280	0.178	0.467	0.104
dlcr	0.347	0.188	0.138	0.367	0.002	0.232
dldr	0.379	0.241	0.333	0.193	0.015	0.273
dlfr	0.177	−0.195	−0.355	0.236	−0.396	−0.076
m3_y3spr	−0.346	0.298	−0.151	0.329	−0.113	−0.030
m3_y10spr	−0.355	0.384	−0.199	0.236	−0.021	−0.022
y3_y10spr	−0.206	0.371	−0.199	−0.053	0.167	0.004
dlsensex	−0.052	0.427	−0.034	0.277	−0.022	0.101
bse_vol	0.302	−0.278	0.068	−0.266	0.082	−0.155
dlcpi	−0.183	−0.074	0.435	−0.175	0.177	−0.004

Table IV. Principal component loadings

domestic residents and credit to commercial sector are positive, signaling that the financial conditions are made better by an increase in credit lending in the economy.

A surprising result was the negative coefficient of market capitalization, though it was quite low and thus can be ignored. The coefficients of three month–three year bond yield spread and three month–ten year yield were, as expected, negative, showing that the financial conditions undergo tightening when the bond yields increase. BSE SENSEX also bears a positive coefficient and shows that loosening of financial conditions stems from increase in financial market activity and an increase in stock market indices.

Similarly, the negative coefficient of volatility of BSE SENSEX shows that volatile markets discourage the investors to invest more funds and thus lead to tightening of the financial conditions.

Table IV lists the loading coefficients of the eigenvectors of the five principal components, while Table AI lists the scoring coefficients. Loading coefficients are the correlations between the original variables and the unit-scaled components. Loadings can be considered as the elements of non-standardized eigenvectors', i.e. eigenvectors generated by corresponding component variances, or eigenvalues. Thus, loading coefficients provide a way to interpret the patterns in the score plot. Scoring coefficients, on the other hand, are row vectors, providing a summary of the relationship among the observed variable values.

The component loading plot and scoring plot in the Figure 4 and Figure A2, respectively, provide a good visual aid to understand the distribution of variable correlations for the first two components (the components with majority of the variance).

Since, all five principal components are orthogonal to each other; factor loadings for a variable in some of the principal components will have negative values. Negative loading of a variable toward a PC would mean that it has a negative relationship with that principal component. But since, ultimately, we use a weighted average of all five PCs as the final FCI, the weighted loading assumes more significance. Thus, the actual importance of each variable in the FCI is equal to the weighted sum of the loadings on each variable across the five principal components.

As stated above, the final column of Table IV shows the weighted loadings in the final FCI. Figures 6 and 7 show the rankings of indicators by their loading values. In Figure 7, the ranking of indicators is by the absolute values of weighted, while in Figure 6 is by the actual values. In about half of the indicator variables, the loading value is negative and the rest are positive. The interest rates and yield spreads generally have negative loadings, while credit to domestic sector, credit to commercial sector, SENSEX, broad money (M3) all have positive

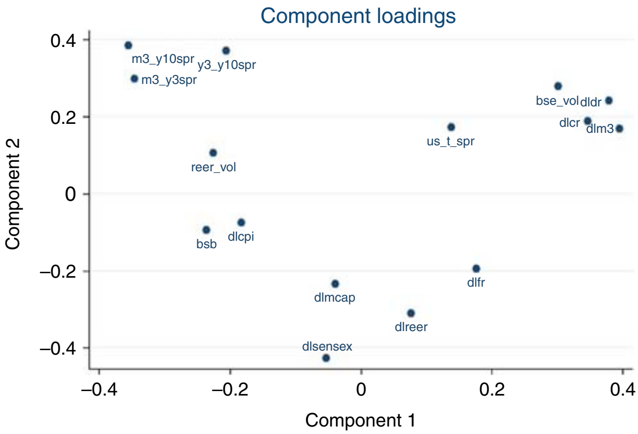

Figure 4.
Loading values plot for two selected components

loadings. Volatilities have a mixed picture as foreign market (REER) volatility is seen to have a positive loading, while BSE SENSEX volatility has a negative loading.

Figure 5 shows the final newly constructed FCI for the Indian economy. As an initial validation of a correlating relationship between the FCI and the recorded growth, the FCI does reach its peak around the years 2005–2008 when the Indian economy had experienced a steady and high growth rate.

The highest value of the index around 2005–2008 can be attributed to the extraordinary growth that the Indian economy experienced during those years. Just after the global financial crisis of 2008, the FCI, as expected, experiences a huge fall from its highest value just before 2008. The index goes on decreasing after 2008 partially due to rising fiscal

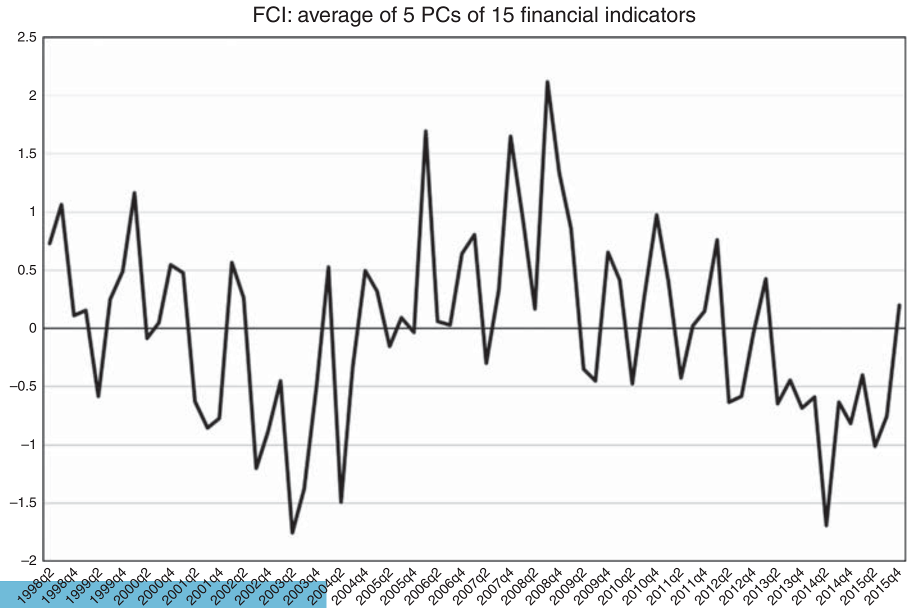

Figure 5.
New FCI: weighted average of five principal components

deficits, peaking inflation, falling Rupee, though it has been showing signs of improvement after late 2014, which can be attributed to change in government at the center in mid-2014.

The FCI is normalized (i.e. de-meaned[23]) before it is reported. Thus, the FCI is reported as the number of standard deviations away from its historical mean (Figures 6 and 7).

5.2 Interpretation of FCI

The newly constructed FCI is a weighted average of 15 indicators of risk, credit and leverage in the Indian financial system. Each of these indicators expressed relative to its sample average and scaled by its sample standard deviation (see Equation (1)). Thus, a zero value for the FCI can be interpreted as the Indian financial system currently operating at historical average levels of risk, credit and leverage.

Similarly, a positive deviation from zero value would reflect easing of financial conditions (meaning lower than average financial stress being prevalent), while a negative value of the index would mean the financial conditions have tightened and would adversely impact the economic growth unless steps are taken to correct the prevalent financial stress.

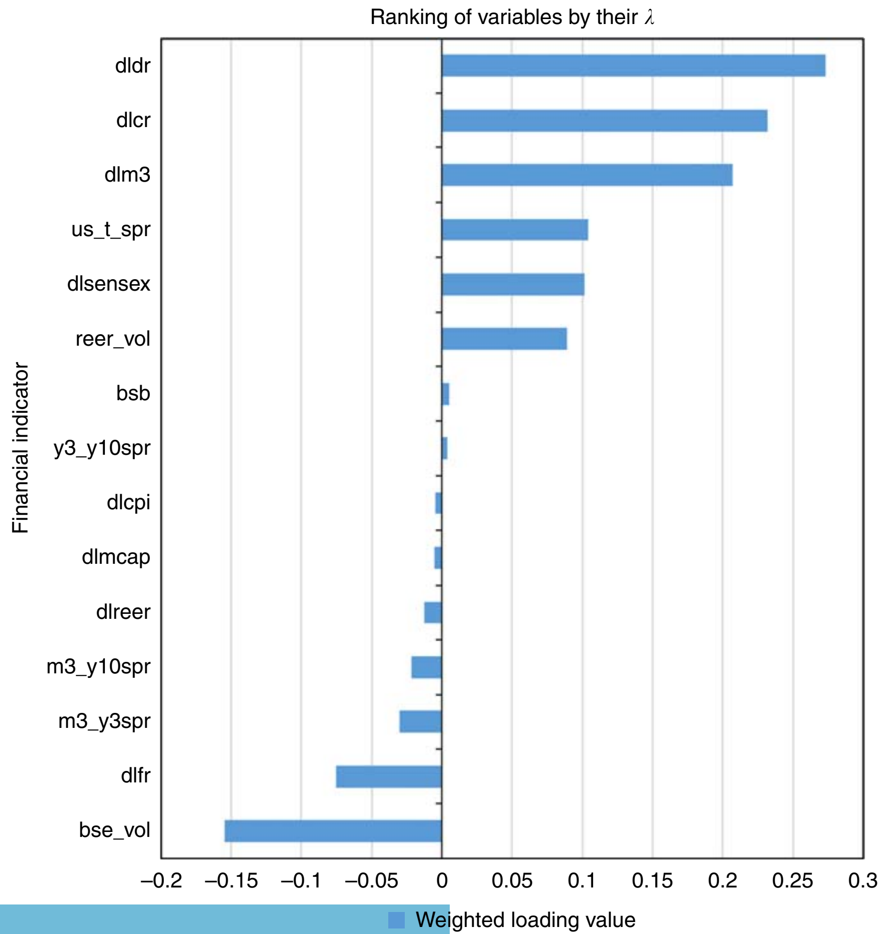

Figure 6.
Ranking of variables by their weighted loading value

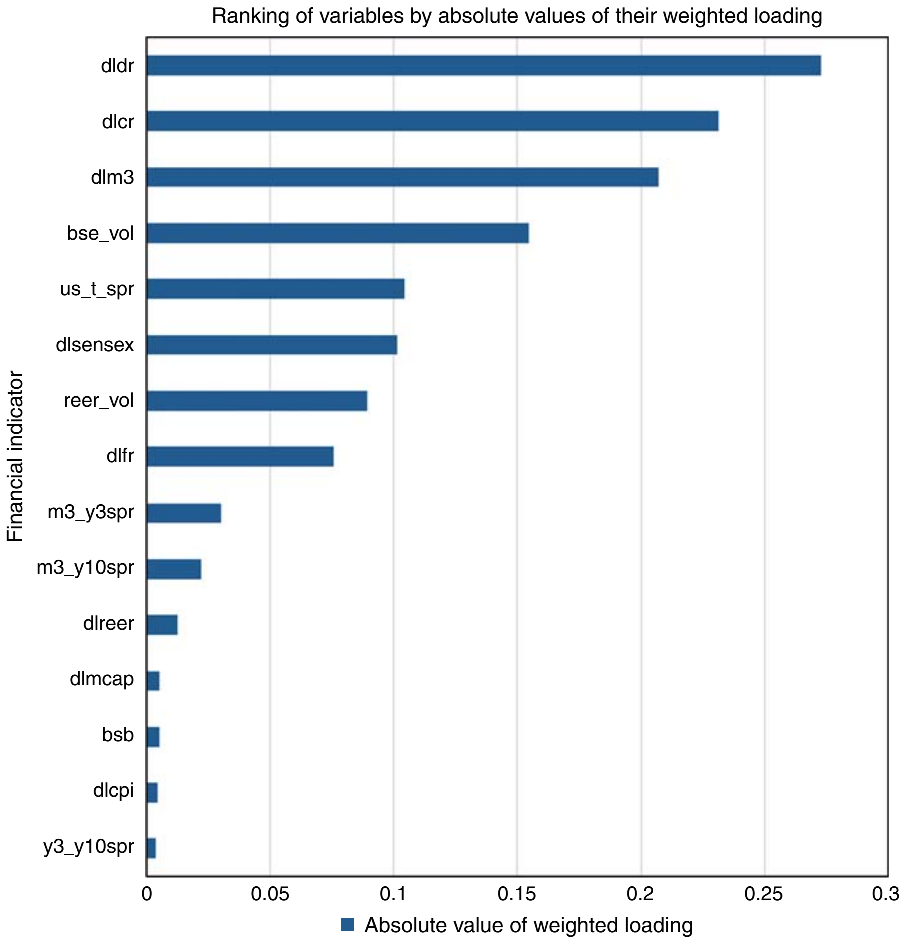

Figure 7.
Ranking of variables by absolute values of their weighted loading value

5.3 Evaluation of FCI as a growth predictor

As mentioned in Section 3, we run the ARDL approach to co-integration to test if the newly constructed FCI can forecast the future economic growth. This would, in turn, make it clear if and how the financial conditions have an impact on the future real economic activity.

As stated in the Section 3.4, the ARDL approach works fine with a combination of I(0) and I(1) variables, but would not work even if any of the variables is I(2). Since we are applying the ARDL approach to co-integration, it is imperative to confirm if both are series, GROW and FCI[24] are not I(2). Table V shows the results of unit root tests like

Table V.
Unit root results

Series	ADF	PP	Stationary
FCI	−2.841 (0.07)	−2.741 (0.08)	Yes
GROW	−1.019 (0.63)	−0.264 (0.89)	No
ΔFCI	−11.21 (0.00)	−17.30 (0.00)	Yes
ΔGROW	−11.26 (0.00)	−29.19 (0.00)	Yes

Augmented Dickey–Fuller (ADF) test and Phillips–Perron (PP) test on level and first-differenced series, in terms of t-statistic reported by the respective test. Both ADF and PP tests define the null hypothesis (H_0) as "Unit root present" and alternate hypothesis ($H1$) as "Unit root absent." In both the aforementioned tests, the level data of GROW fail to reject the null hypotheses, confirming that GROW is not I(0). On the other hand, FCI's level data reject the null hypothesis but only at 10 percent significance. Both the series comfortably reject the null hypotheses of both the tests when first-differenced confirming that none of them is I(2) and thus can safely be used to test the presence of co-integration using the ARDL approach.

Now, we estimate the ARDL bounds test approach to co-integration. We estimate Equation (5) using OLS (as per the methodology explained in Section 3.4) and the joint significance of the parameters of lagged variables in the equation is tested for. Note that, here (as mentioned in Section 3.3) we only test for joint significance of δs only and not of other parameters. ARDL does have some assumptions about the data series used in the estimation. The results in Table VI can be used to verify if both our series' satisfy the required assumptions for ARDL approach.

The ARDL bounds test results show the value of F-statistic as 4.2486(0.02). This value is greater than the tabulated critical values in the works of Pesaran *et al.* (2001) and Narayan (2004). This confirms the presence of co-integrating relationship between our FCI and the real GDP's growth rate.

Table VII reports the long-run coefficient for FCI and the related t-value estimated from the ARDL test. The positive coefficient confirms the positive long-run relationship between the FCI and the growth rate of the Indian economy's real GDP. The t-statistic value of 7.60 confirms that the coefficient is indeed significant and thus can be used in further calculations.

Table VIII presents the short-run coefficient for FCI and the related t-value estimated from the ARDL test. Similar to the results in long run, the positive coefficient confirms the positive relationship between the FCI and the growth rate of Indian economy's real GDP. The t-statistic value of 1.91 confirms that the coefficient is significant[25].

Diagnostic test	
Normality J-B value	5.3211 (0.210)
Serial correlation LM test	1.3100 (0.252)
Heteroscedasticity (ARCH)	4.2682 (0.118)

Table VI. Diagnostics test for ARDL bounds test

Regressor	Coefficient	t-statistic (p-value)
FCI	0.0616	7.5982 (0.001)

Note: Dependent variable is GROW

Table VII. Estimated long-run coefficients

Regressor	Coefficient	t-statistic (p-value)
ΔGROW	−0.3341	−2.9490 (0.004)
ΔFCI	0.0759	1.9060 (0.060)
ecm(−1)	−0.123	−2.0150 (0.048)

Note: Dependent variable is GROW

Table VIII. Error correction model of ARDL

The stability of ARDL results was tested and the results for that test are attached in appendices (see Table AIV) (Figure 8).

The solid line represents the quarter-on-quarter (Q/Q) growth rate of real GDP while the dotted line represents the growth rate predicted by the FCI[26]. As seen in the graph, FCI-predicted values follow a trend that is very similar to the actual values. Also, as seen in the graph, the FCI-predicted values tend to over-estimate the depressions while under-estimate the peaks. Through its predictive power, the newly constructed FCI makes a good case for it to be used as a policy tool by the Reserve Bank of India.

5.4 Comparison with FDI

To confirm that looking at other markets like bond markets, foreign exchange markets etc., is important to build a growth-predicting index, we build a FDI which focuses on variables which signal development of financial/stock markets alone. The construction of FDI uses the standard PCA methodology as a balanced panel of data was available starting 1999q1. We employ a similar model as we did for FCI's evaluation and try to predict the growth of real GDP. Figure 9 depicts the predictive power of FDI. As seen from the two forecasts by FCI and FDI as the long-run coefficient of the ARDL model for FDI is not significant even at 10 percent and FCI clearly predicts the growth in real GDP better than the FDI which focuses only on specific markets and fails to accurately summarize the comprehensive conditions prevailing in the economy. Further, in the context of open economy macroeconomics, the inclusion of both domestic and foreign economy parameters help understanding the economic growth and development of the developing economy like India. This is one of the reasons why FCI explains economic growth better than FDI in the context.

Table IX lists the long-run coefficient of FDI when regressed with GROW using the ARDL approach.

6. Conclusions and summary

The recent global financial crisis underscored the need for monetary policy authorities to have for a comprehensive view of the conditions prevailing in the economy before deciding their policy stance. Interest rate targeting may not always be useful and possible in the wake of events involving financial stress. Recently, though financial stress might not be directly conceivable, much research has gone into trying to summarize the stress in the financial

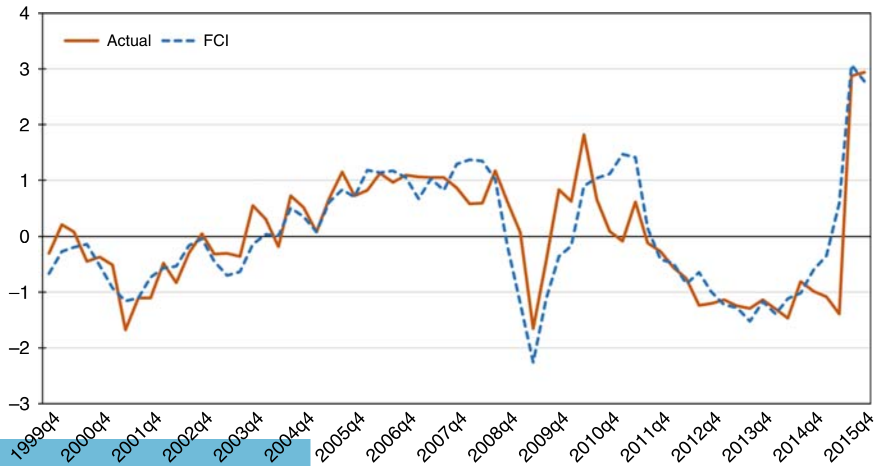

Figure 8.
Real GDP growth: forecast using FCI

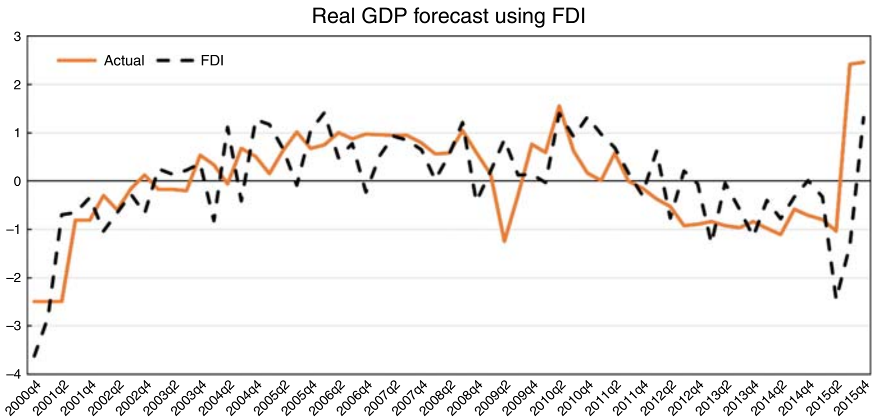

Figure 9.
Real GDP growth: forecast using FDI

Regressor	Coefficient	*t*-statistic (*p*-value)
FDI	0.1525×10^{-3}	0.86322 (0.731)

Note: Dependent variable is GROW

Table IX.
Estimated long-run coefficients

market variables by a way of a single index. The rationale for the inclusion of a broad range of indicators of financial conditions is grounded in the theoretical literature and it is premised in the concept that market imperfections imply a need to look beyond simply prices (interest rates) as measures of financial market conditions. In this study, we outlined the construction of similar index called the FCI for the Indian economy taking into account a variety of indicators from different markets. This index is the synthesis of information content in the money, bond, foreign exchange and stock markets. The index shows that tight financial conditions in one market can off-set accommodative conditions in some other market thereby making the aggregate conditions tight. Therefore, it is necessary to account for financial conditions in all markets simultaneously in the conduct of policy. The paper also poses some interesting research questions in context of interaction of financial conditions and real variables like GDP growth. Hence, we believe that the growth-predicting power of the newly constructed quarterly FCI for Indian economy would enable the Reserve Bank of India and Monetary Policy Committee (MPC) to forecast the real GDP in advance and help them design appropriate policy changes so as to stay on course for achieving the MPC's long-term targets if they are not being met.

The comparison of predictive powers of a narrow index like FDI and newly constructed FCI proves that the traditional monetary policy targets need to be expanded in favor of a more comprehensive index of the conditions currently prevailing in the economy. The Indian economy is more venerable to changes in the international market condition in the recent past. Hence, taking into account the conditions in all the markets is necessary to predict the real sector growth.

Going forward, we believe a more enhanced FCI which tracks and includes more number of indicators can be constructed. Defining upper and lower bounds/critical values for deciding upon likely events of financial stress is an interesting research problem that can be looked at. Including specific indicators to track stress in the economy in construction of FCI can help build a more effective FCI and can then be used for defining a mitigating or exiting strategy for steering the Indian economy out of a crisis.

FCI provides a more comprehensive framework in which to understand the economic environment rather than narrow measures such as FDI which based solely on interest rates or money supply. In particular, FCI takes into account that the exchange rate has gradually become a more important determinant of financial conditions, and that money supply is an independent transmission channel apart from interest rates. It also takes into account the evolving dynamics in the relationship between the variables in the economy, and is fairly simple and transparent in construction. FCI would act a useful tool to judge the monetary policy stance, based on clear assumptions and historical relationships. Investors can use the FCI and especially deviations in the paths of forecast variables to form a view on the path of policy, growth and inflation

Notes

1. Tracked by the amount of credit provided to residents.
2. Separately from the financial conditions index (FCI).
3. Other methods and their usage in literature have been mentioned in the previous section.
4. For example, house price index is only available from 2009q2.
5. This involves loss of information as we do not use all the indicators, but this loss is made up for in the later steps.
6. Using simple OLS estimation.
7. The Kaiser–Guttman rule (Kaiser, 1957, 1991) says that we should consider only the components which have an eigenvalue of more than unity.
8. We look for an "elbow" in the scree plot. It helps to gauge which components are explaining most of the variance. See Figure 3 for example.
9. See Equation (1) for the normalization procedure.
10. Henceforth labeled as GROW.
11. We use the Schwartz information criterion (SIC) (Schwarz, 1978) to fix the lag order.
12. The earliest data point for a series is for 1991q1, while the original balanced panel is available only from 2001q1.
13. These indicators also help track the bond market sentiment.
14. All the yields used are for government/treasury-issued bonds.
15. For private players, a spread between corporate bond yields over risk-free government securities would provide better representation, but has not been considered in this study owing to limitations of data.
16. This also helps tracking the equity markets.
17. The degree to which a company uses fixed-income securities such as debt and preferred equity.
18. The increase in credit lending amount would bring in interest rate effect and would help to reflect the entrepreneurial sentiment in the economy.
19. This is specially included to track the strength and performance of banks, which remain at the center of financial systems in the Indian economy.
20. Represented through BSE SENSEX's first-differenced values.
21. After applying transformation stated in Table I.
22. Originally unbalanced, missing values filled according to the Step 4 in Section 3.2.

23. See Equation (1) in Section 3.
24. Reported as standardized value of FCI.
25. The coefficient is significant at 10 percent.
26. This is done using the long-run coefficients from Table VII.

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Appendix 1. Principal components analysis (PCA)

Loading and scoring matrix

Formally, PCA can be viewed as decomposition of the indicator values matrix X into two matrices U and V, such that:

$$X = V^T \times U, \tag{A1}$$

where matrices U and V are orthogonal. U is called the scoring matrix and V is called the loading matrix. Thus, the loading matrix V holds the weights of original variables that will be used while calculating the principal components, whereas the scoring matrix U holds the original data in a rotated coordinate system.

This can be better visualized using Figure A1.

Summary of PCA

Eigenvalue decomposition of covariance (or correlation) matrix provides for the (principal) components for the observed set of variables. Each one of these components are in fact a linear combination of the original variables. The first of these components (when ordered by decreasing eigenvalues) is a unit length vector (linear combination), which explains the maximum variance amongst the variable series'. All the subsequent components are orthogonal to the first component and each one of the subsequent component would maximize the variance accounted from the remaining of the original variance (and are ideally uncorrelated with the previous components). The first few components (which explain

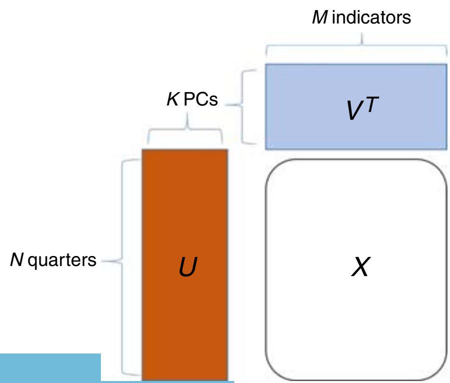


Figure A1. Loading and scoring matrix majority of the variance) are termed as principal components and are be used in further analysis as they are or by forming a single variable by taking a weighted average of these principal components. We follow the approach of constructing a single variable in our analysis.

Appendix 2. Additional results

Scores matrix and plot

The component loading plot (shown earlier) and scoring plot in Figure A2, respectively, provide a good visual aid to understand the distribution of variable correlations for the first two components (the components with majority of the variance) (Table AI).

Correlation matrix

The correlation matrix represents the pair-wise inter-indicator correlation amongst all the 15 indicators used in construction of index. Generally, more correlation amongst the variables used in PCA tends to produce principal components that explain the majority of variance in the lesser number of principal components (Tables AII and AIII).

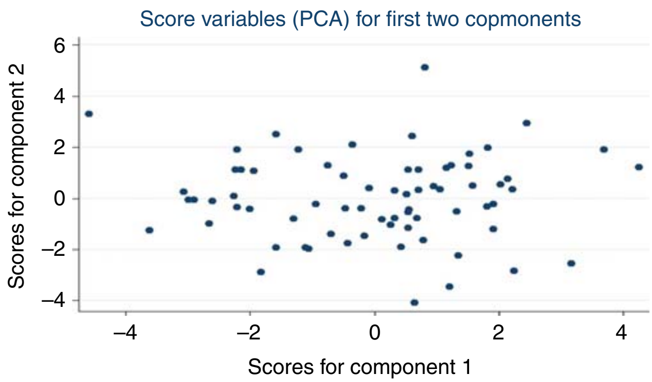


Figure A2.
Score values plot for first two components

Variable	Comp1	Comp2	Comp3	Comp4	Comp5
dlm3	0.396	0.169	0.049	0.293	−0.075
dlreer	0.077	−0.311	−0.114	0.145	0.471
reer_vol	−0.226	0.105	0.422	0.170	0.273
bsb	−0.236	−0.094	0.412	0.397	−0.272
dlmcap	−0.039	−0.234	−0.078	0.321	0.412
us_t_spr	0.138	0.173	−0.280	0.178	0.467
dlcr	0.347	0.188	0.138	0.367	0.002
dldr	0.379	0.241	0.333	0.193	0.015
dlfr	0.177	−0.195	−0.355	0.236	−0.396
m3_y3spr	−0.346	0.298	−0.151	0.329	−0.113
m3_y10spr	−0.355	0.384	−0.199	0.236	−0.021
y3_y10spr	−0.206	0.371	−0.199	−0.053	0.167
dlsensex	−0.052	−0.427	−0.034	0.277	−0.022
bse_vol	0.302	0.278	0.068	−0.266	0.082
dlcpi	−0.183	−0.074	0.435	−0.175	0.177

Table AI.
Scoring coefficients

Variable	dlm3	dlreer	reer_vol	bsb	dlmcap	us_t_spr	dlcr	dldr
dlm3	1.0000							
dlreer	0.0066	1.0000						
reer_vol	−0.0957	−0.0294	1.0000					
bsb	−0.1078	−0.0981	0.4617	1.0000				
dlmcap	−0.0910	0.2518	0.0163	0.0718	1.0000			
us_t_spr	0.2225	0.0237	−0.1815	−0.3946	0.0226	1.0000		
dlcr	0.4887	0.0202	−0.0983	−0.0370	−0.0903	0.2489	1.0000	
dldr	0.6794	−0.1588	0.1068	−0.0216	−0.1459	0.1215	0.7210	1.0000
dlfr	0.2517	0.1672	−0.4272	−0.1473	0.1255	0.0423	0.0868	−0.1275
m3_y3spr	−0.2429	−0.3008	0.1715	0.2133	−0.0139	0.1148	−0.1010	−0.2401
m3_y10spr	−0.2052	−0.2970	0.2156	0.1256	−0.0684	0.1390	−0.1427	−0.2555
y3_y10spr	−0.0368	−0.1511	0.1998	−0.1020	−0.1416	0.1208	−0.1563	−0.1659
dlsensex	−0.1337	0.2562	−0.0687	0.2489	0.2879	−0.0275	−0.2127	−0.2713
bse_vol	0.4178	−0.2354	−0.1212	−0.3456	−0.1098	0.1315	0.2790	0.4960
dlcpi	−0.2982	−0.0976	0.3412	0.3665	−0.0008	−0.1454	−0.1536	−0.0457

Table AII. Correlation matrix

Variable	dlfr	m3_y3spr	m3_y10spr	y3_y10spr	dlsensex	bse_vol	dlcpi
dlfr	1						
m3_y3spr	−0.1501	1					
m3_y10spr	−0.1879	0.9244	1				
y3_y10spr	−0.173	0.3471	0.6786	1			
dlsensex	0.1865	−0.1477	−0.2729	−0.3863	1		
bse_vol	−0.105	−0.1997	−0.1326	0.0587	−0.3746	1	
dlcpi	−0.3592	−0.02	−0.0714	−0.1369	−0.0033	−0.1196	1

Table AIII. Correlation matrix – contd

KMO measure of sampling adequacy

The Kaiser–Meyer–Olkin (KMO) test for sampling adequacy developed by Cerny and Kaiser (1977) is used to test whether the data are suited for applying principal component analysis. It tests how the partial correlation of a few variables is affected by other variables and whether there exists a possibility of summarizing the information in fewer principal components.

The test results are reported in Table AIV. The KMO values for most of our variables are in the "miserable" bracket but we consider them since they are almost bordering on a "mediocre" level. The overall value also lingers very close to the "mediocre" bracket and so can be considered acceptable.

Stability test for the ARDL approach

The stability of the ARDL procedure results is evaluated using the cumulative sum of recursive residuals (CUSUM) and its square (CUSUMSQ) tests proposed by Brown *et al.* (1975). The results are expected and thus confirm the stability of results (Figures A3 and A4).

Variable	KMO	Variable	KMO
dlm3	0.5921	dldr	0.5631
dlreer	0.5322	dlfr	0.5506
reer_vol	0.6138	m3_y3spr	0.5205
bsb	0.5194	y3_y10spr	0.5068
dlmcap	0.545	dlsensex	0.6367
us_t_spr	0.5578	bse_vol	0.7959
dlcr	0.5302	dlcpi	0.6732
m3_y10spr	0.4508	Overall	0.5946

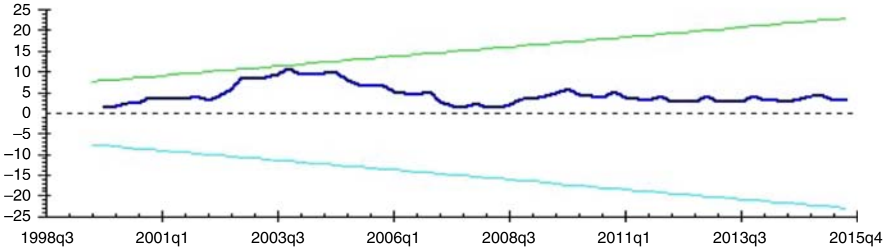
Table AIV. Kaiser–Meyer–Olkin measure of sampling adequacy

Financial development index (FDI) construction

For the construction of FDI, a standard PCA procedure is applied using three indicators, namely, credit to domestic residents, market capitalization and broad money (M3) for the period 1999q1–2015q4.

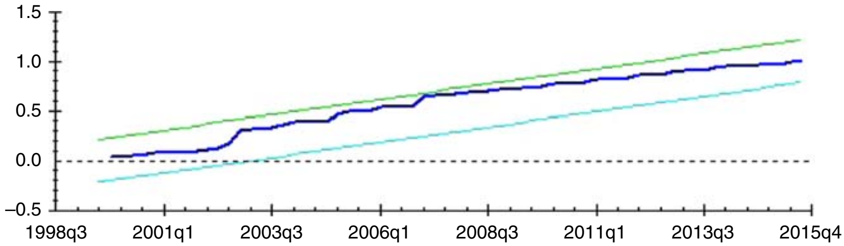
The eigenvalue/eigenvector table and loadings matrix are shown below in Tables AV and AVI, respectively.

Appendix 3. Final FCI values



Note: The straight lines represent critical bounds at 5 percent significance level

Figure A3.
Plot of cumulative sum of recursive residuals



Note: The straight lines represent critical bounds at 5 percent significance level

Figure A4.
Plot of cumulative sum of squares of recursive residuals

Table AV.
Principal components/correlation

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.90817	2.81714	0.9694	0.9694
Comp2	0.09103	0.09024	0.0303	0.9997
Comp3	0.00080		0.0003	1.0000

Notes: Number of obs = 68; number of components = 1; trace = 3; $\rho = 0.9694$; rotation: (unrotated = principal)

Table AVI.
Principal component loading

Variable	Comp1	Wtd loading
dlm3	0.5827	0.5827
dldr	0.5812	0.5812
dlmcap	0.5681	0.5681

Quarter	FCI	Quarter	FCI	Quarter	FCI
1998q2	0.7330	2004q2	−1.4884	2010q2	−0.4723
1998q3	1.0673	2004q3	−0.3303	2010q3	0.2647
1998q4	0.1130	2004q4	0.4963	2010q4	0.9751
1999q1	0.1525	2005q1	0.3215	2011q1	0.3992
1999q2	−0.5797	2005q2	−0.1540	2011q2	−0.4219
1999q3	0.2507	2005q3	0.0951	2011q3	0.0216
1999q4	0.4873	2005q4	−0.0323	2011q4	0.1491
2000q1	1.1631	2006q1	1.6923	2012q1	0.7619
2000q2	−0.0841	2006q2	0.0579	2012q2	−0.6335
2000q3	0.0481	2006q3	0.0289	2012q3	−0.5838
2000q4	0.5465	2006q4	0.6444	2012q4	−0.0467
2001q1	0.4784	2007q1	0.8061	2013q1	0.4240
2001q2	−0.6243	2007q2	−0.3015	2013q2	−0.6434
2001q3	−0.8545	2007q3	0.3312	2013q3	−0.4416
2001q4	−0.7700	2007q4	1.6486	2013q4	−0.6830
2002q1	0.5689	2008q1	0.9224	2014q1	−0.5862
2002q2	0.2657	2008q2	0.1691	2014q2	−1.6943
2002q3	−1.1991	2008q3	2.1168	2014q3	−0.6354
2002q4	−0.8877	2008q4	1.3355	2014q4	−0.8170
2003q1	−0.4500	2009q1	0.8558	2015q1	−0.3967
2003q2	−1.7552	2009q2	−0.3514	2015q2	−1.0123
2003q3	−1.3809	2009q3	−0.4498	2015q3	−0.7525
2003q4	−0.4797	2009q4	0.6561	2015q4	0.2002
2004q1	0.5310	2010q1	0.4142		

Table AVII.
Calculated FCI values

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