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Revisiting the Long-Run Dynamic Linkage between Dividends and Share Price with Advanced Panel Econometrics Techniques

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Abstract: The log-linearized present value model (PVM) has been widely used in corporate finance to understand the long-run relationship between share price and dividends using panel data. However, the application of recently established panel econometric approaches that account for slope heterogeneity and cross-section dependency in the recent literature regarding the long-run link between share price and dividends in an Indian setting is limited. This paper re-examines the log-linearized PVM in an Indian setting using newly developed panel unit root, cointegration, and long-run dynamic estimation approaches. This study employed a panel dataset of 60 Bombay Stock Exchange (BSE)-listed Indian firms paying regular dividends for 28 years (1990–2017). The study found unit root, cointegration, and a long-run relationship between dividend and share price series for Indian firms during a 28-year sample period. By demonstrating the presence of a long-run link between share price and dividends, this paper contributes to the literature on the PVM, which is crucial in comprehending market rationality and share price behavior in India. This paper also discusses issues related to panel data, such as cross-section dependency and slope heterogeneity, as well as panel econometric approaches that can be applied in the appropriate settings.

Keywords: log-linearized present value model; share price; dividends; Indian firms; long-run relationship; second-generation panel unit root and cointegration tests; dynamic CCEMG model

1. Introduction

The simple present value model has been widely used by academicians and econometricians to understand the contribution of dividends paid by corporate firms to explaining the fluctuations in stock prices. The simple present value model relates the current stock price to the future dividends discounted at a constant discount rate. Shiller (1981) described the present value model as an efficient market model since it helps to explain the variations in stock prices from its fundamental value in relation to any new information on fundamentals itself, and the author applied the model to explain market rationality and the behavior of stock prices.

Shiller (1981) applied the variance bounds test and compared the ex-post rational share price or the present value of future dividends with the ex-ante share price or the real share price. The author found the real share price too volatile to be explained by the dividend alone. This finding led to enormous amounts of academic research on the relationship between share price and dividends using the present value model. In that direction, Campbell and Shiller (1987) investigated the validity of the simple present value model by testing for the presence of cointegration between I (1) stationary real share price and real dividends when the discount rate is assumed to be constant. Later, Campbell and Shiller (1988) developed the log-linearized version of the simple present value model, which assumed a time-varying rather than a constant discount rate. The rationale for developing the log-linearized present value model (PVM) was to make it more conducive to empirical examination by testing for I (0) stationary of either the difference between the log real share price and log real dividend or the log price-dividend ratio. The presence of

cointegration between the share price and dividends would ensure that an equilibrium relationship is maintained between the two variables in the long run. Hence, any shock to a cointegrated process will not have a lasting impact. Therefore, any temporary deviation of the share price from its fundamental values will eventually bring it back into equilibrium in the long run.

Many authors have attempted to examine the validity of both the simple and log-linearized versions of the present value model using aggregate and firm-level data and have found evidence both in favor of and against the validity of the present value model. This includes the studies of Phillips and Ouliaris (1988), Campbell and Shiller (1987, 1988), Diba and Grossman (1988), Froot and Obstfeld (1991), Craine (1993), MacDonald and Power (1995), Lamont (1998) and Marsh and Power (1999) etc. More recently, the studies include Balke and Wohar (2001, 2002); Nasseh and Strauss (2004); Goddard et al. (2008); McMillan (2010); Nirmala et al. (2014); Esteve et al. (2017); Persson (2015); Charteris and Chipunza (2020), etc.

In the context of emerging markets such as India, very few studies have recently been conducted to test the validity of the log-linearized present value model. Therefore, to analyze and re-examine the relevance of the log-linearized version of the present value model (PVM) in the context of Indian firms, this study uses sample panel data of selected Indian firms listed on the Bombay Stock Exchange (henceforth, BSE) with an annual time series from 1990 to 2017. The goals of this study are as follows: (a) testing for cointegration between log real share price and log real dividend using a newly developed second-generation panel unit root and cointegration technique; and (b) establishing the long-run relationship using panel cointegration regression. For examining the second objective, a long-run relationship estimation method used in the paper by Eberhardt and Presbitero (2015) was employed. The authors have applied Chudik and Pesaran's (2015) dynamic CCEMG model with an error-correction term to estimate and evaluate the debt–growth nexus. The above method addresses the issues of cross-section dependency and slope heterogeneity that are specific to panel time-series data.

This paper's contribution to the existing literature on establishing a long-term relationship between share price and dividends using the present value model can be explained as follows. First, the paper's findings may help academicians and practitioners comprehend the role fundamentals such as dividends play in explaining long-term share price fluctuations, particularly in emerging markets such as India. This could aid in a better assessment of market rationality and stock price behavior in the Indian market. Second, understanding the long-term relationship between dividends and share prices may aid Indian corporations and managers in formulating more effective dividend policies, which may ultimately lead to higher share price valuations.

The rest of the paper is arranged accordingly. Section 2 outlines the theoretical model of PVM, and the empirical literature associated with PVM. Section 3 outlines the panel econometric approach applied to the paper and issues related to it. In Section 3 of this paper, Sections 3.1–3.3 describe the necessary panel econometrics strategies and tests, such as the cross-section dependency test, first-and second-generation panel unit root and cointegration tests, and long run estimation strategies, used to get the necessary results. Section 4.1 sheds light on the data used in the paper, and Section 4.2 presents the results and findings in tables (1-8) and discusses them in terms of the empirical approaches used. Section 5 finally provides a brief conclusion of the study.

2. The Present Value Model: Theory and Empirical Literature

The present value model can be expressed as: the current value of stock price (P_t) is a function of the discounted value of expected dividends discounted at a constant rate. This definition can be expressed as:[1]

$$P_t = \sum_{i=1}^{\infty} \delta^i E_t D_{i,t+i} \tag{1}$$

where P_t is the discounted value of expected dividends, $\delta = \left(1 + \frac{1}{R}\right)$ is the constant discount rate and D_{t+i} is the dividend paid at the period $t + i$. Shiller (1981) applied the variance bounds test and compared the ex-post rational stock price or the discounted value of future dividends with the ex-ante share price or the actual share price. According to Shiller (1981), if Equation (1) remains true, the discounted value of expected dividends should be equal to the actual stock price plus any unexpected noise, and so should be more volatile than the actual stock price. On the contrary, the author found the ex-ante stock price was too volatile to be explained by the dividend. This finding led to an enormous amount of academic research on the relationship between stock price and dividends using the present value model. His work was later criticized by Kleidon (1986) and Marsh and Merton (1986) on the grounds that the variance bounds test requires the dividend process to be stationary. Following the criticism and non-stationarity issue of the dividend process, Campbell and Shiller (1987) modified the present value model with the following adjustment by subtracting, $D_t R^{-1}$ from both sides of Equation (1):

$$P_t - D_t R^{-1} = R^{-1} E_t \sum_{i=0}^{\infty} (1 + R)^{-i} \, \Delta \, D_{t+i} \tag{2}$$

The resulting differential Equation (2) shows that if the dividend process is I(d) stationary and the discount rate is constant, the real stock price and real dividends will be cointegrated with the cointegration vector (1,-1/R) and the present value model will be valid. Campbell and Shiller (1987) tested for cointegration using Engle and Granger's (1987) residual-based cointegration test. Their results were ambiguous. They were unable to reject the null hypothesis of no cointegration at a 10% level of significance at a constant mean. They concluded that the evidence of cointegration between stock price and dividends would be weaker than the evidence of cointegration in the term structure of interest rates. Following Campbell and Shiller (1987), Diba and Grossman (1988) investigated the cointegration relationship between stock price and dividends using the Engle and Granger (1987) and Bhargava (1986) tests. While their Engle and Granger (1987) test gave mixed results, the Bhargava (1986) test provided evidence in favor of cointegration between stock price and dividends. Phillips and Ouliaris (1988) applied a newly developed approach of principal component analysis for testing the presence of cointegration between real stock price and dividends, and their result was compatible with Shiller (1981).

Additionally, MacDonald and Power (1995) examined the cointegration between real stock price and real dividends in the presence of retained earnings. They also found no evidence of cointegration of real stock price and real dividends. However, they mentioned the existence of a unique cointegration relationship between stock prices and dividends when retained earnings were included in the equation. Sung and Urrutia (1995) also explored the existence of bi-directional causality between stock price and dividend. They observed cointegration between stock price and dividends and significant bi-directional causality between both the variables.

To explore the nonlinear cointegration between real stock price and dividends, a few more authors, such as Kanas (2003), applied the ACE transformation algorithm to induce nonlinearities among the variables and test for cointegration. He found strong evidence of nonlinear cointegration between variables. Kapetanios et al. (2006) used a newly developed nonlinear smooth transition autoregressive error-correction-based model (STAR-ECM) to test the nonlinear cointegration between real stock price and real dividend. They applied the test to stock price and dividend data for 11 stock markets across the world. For the majority of stock markets, the authors found strong evidence of nonlinear cointegration between real stock price and real dividends over linear cointegration.

To make the PVM more practical for empirical evaluation, Campbell and Shiller (1988) developed the present value model in a log-linearized framework using the first-order Taylor series approximation, which allows the discount rate to be time-varying instead of constant. The log-linearized PVM is as follows:

$$p_t = \left[\frac{k}{1-\rho}\right] + E_t \left[(1-\rho)\sum_{i=0}^{\infty}\rho^i d_{t+i+1} - \sum_{i=0}^{\infty}\rho^i r_{t+i+1}\right] \tag{3}$$

where the lower-case letters p, d, and r represent the natural log of price, dividends, and discounting factor respectively. κ and ρ are linearized parameters, $\kappa = -ln(\rho) + (1-\rho)ln(\rho-1)$ and $\rho = \frac{1}{[exp(\bar{d}-\bar{p})]}$. With no bubble transversality condition applied to Equation (3), this means the price term on the right-hand side does not exhibit explosive behavior.

Hence, Equation (3) can be rearranged into:

$$p_t - d_t = -\kappa(1-\rho)^{-1} + E_t \sum_{i=0}^{\infty}\rho^i(\Delta d_{t+i+1} - r_{t+i+1}). \tag{4}$$

This above representation of the present value model states that considering the discount rate and dividend growth term on the right-hand side of Equation (4) are I(0) stationary, the log price–dividend ratio (pd_t) on the left-hand side of Equation (4) would also be I(0) stationary, and the log real stock prices and log real dividends would cointegrate with the cointegrating vector of $(1,-1)$ when the log real stock price and log real dividend are I(1) nonstationary. Hence, testing for the present value model would require only testing for the stationarity of the log price-dividend ratio. Many authors tested the notion of stationarity of pd_t and they found a significant degree of persistence in the pd_t series. Froot and Obstfeld (1991) applied a unit root test to the price–dividend ratio both at level and log value, and they were unable to reject the presence of a unit root in the price-dividend ratio. Hence, they too put forth the argument that stock prices are too sensitive to be explained by the current dividend process. Along with Froot and Obstfeld (1991), similar conclusions were drawn by Craine (1993), Lamont (1998), and Balke and Wohar (2001, 2002). McMillan (2010) examined the presence of unit root in both log dividend yield and residuals from cointegration regression of log real stock prices and log real dividends using 10 industry sectors in the UK market. The author concluded that his results support the present value model in its weak form. Esteve et al. (2017) applied a linear cointegrated regression model with multiple structural changes to verify the validity of PVM using annual data of log stock prices and log dividend series of the US stock market for a sample period of 1871–2012. Their results support the presence of linear cointegration between the log stock prices and the log dividends. However, they provided evidence in favor of a weak PVM with multiple structural breaks in the long-term relationship between log real share price and dividends.

With mixed empirical evidence of a cointegration relationship between stock price and dividends when using aggregate data, many authors advocated using firm-level data instead of aggregate data to improve cointegration results (see Jung and Shiller 2005; Vuolteenaho 2002). Marsh and Power (1999) applied a panel cointegration test to 56 large UK firms. They reported the presence of cointegration between real stock prices and real dividends for the UK firms. Nasseh and Strauss (2004) applied panel cointegration techniques to 84 US firms and found significant evidence of cointegration between stock prices and dividends. Goddard et al. (2008) applied a second-generation panel unit root test to the residuals from cointegration regression to 104 UK firms, and their results strongly support the present value model at the firm level. Goddard et al. (2008) provide an argument in favor of the application of cross-sectionally augmented panel unit root and cointegration tests as a means to control the effect of non-fundamental elements, which are the reason for deviations from the long-run equilibrium price–dividend relationship. Outside US and UK stock markets, Nirmala et al. (2014) investigated the long-run and short-run relationship between dividend per share and share price for Indian firms in four sectors: capital goods, healthcare, metal, and public sector undertaking. They found significant linear cointegration relations and bi-directional causality between both the variables in all four sectors. They used annual data for 20 years.

Persson (2015) examined the bi-directional long-term relationship between dividends and share price using 228 UK firms listed on the FTSE ALL SHARE for the sample period

of 1990–2014. The author used both first- and second-generation panel unit root and cointegration tests to test the validity of PVM and further applied the panel vector error-correction model to study the bi-directional long-term causality between dividends and share price. The author confirmed the validity of PVM in 228 UK firms and found a bi-directional long-term causality between dividends and share price.

Very recently, Charteris and Chipunza (2020) tested the validity of PVM in major South African firms listed on the Johannesburg Stock Exchange (JSE) for a period of 20 years. They applied both first- and second-generation unit root and cointegration tests to their firm-level data. They too found evidence in support of PVM with respect to the South African firms. However, with respect to establishing a long-term relationship between share price and dividends, their model falls short of a one-on-one long-term relationship between share price and dividends. Their overall result agrees with the consensus on the validity of PVM in the case of South African firms.

3. Empirical Methodologies and Related Issues

3.1. Cross-Section Dependence and Slope Heterogeneity

For the relevant examination of the present value model, Section 2 has described the importance of employing firm-level data rather than pure time-series data. Baltagi and Kao (2001) explained the importance of adding a cross-section dimension with the time dimension, which will not only increase the number of observations but also enhance the power and size of different time-series unit root and cointegration tests.

However, overlooking certain issues such as cross-section dependence (henceforth, CSD) of errors and slope heterogeneity associated with panel time-series data could be a fundamental problem with the application of panel time-series econometrics when the variables are nonstationary.[2]

The problem of CSD arises when the errors are correlated across individual panel members due to an unobserved common factor or a global or local spillover effect (Phillips and Sul 2003; Andrews 2005; Baltagi and Pesaran 2007). Problems associated with assuming independence of the cross-section in the case of nonstationary panels could pose a threat of severe size distortion while conducting panel unit root and cointegration tests.[3] To check the presence of cross correlation of error terms across panels, Pesaran (2004) developed a cross-section dependence test (or CD test) based on the Lagrange multiplier (LM) test of Breusch and Pagan (1980).

In Pesaran (2004), the CD test statistic is presented as:

$$\text{CD} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right)$$

With, $\hat{\rho}_{ij}$ being the sample estimate of the pairwise correlation of the residuals obtained from individual OLS regression. Unlike other tests for CSD, the Pesaran (2004) test can be applied to a wide range of panels.

However, the Pesaran (2004) CD statistic test is only for the null of cross-section independence over the alternative of presence of strong dependence among error terms across panel. In case of panels with large N and T testing, the null hypothesis of cross-section independence is considered very restrictive. Later, Pesaran (2015) eased the restriction of null cross-section independence and allowed for testing the null of weak cross-sectional dependence or errors.[4] So, the Pesaran (2015) CD test statistic is specified as:

$$\text{CD} = \left[\sqrt{\frac{TN(N-1)}{2}} \right]^{1/2} (\hat{\bar{\rho}}_N)$$

With $\hat{\bar{\rho}}_N$ as the average pairwise correlation given by:

$$\frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij},$$

In parallel to Pesaran (2015), Bailey et al. (2016) developed a method of estimating the exponent of cross-section dependence α, to measure the degree of cross-section dependence of error. When the value of α lies in between 0–1/2, the degree of dependence of errors is considered to be weak, and when it lies in between 1/2–1, the degree of dependence is considered to be strong. Bailey et al. (2016) provide a bias-corrected estimate of α or $\hat{\alpha}$ to test for the degree of cross-section dependence.

Pesaran (2015) pointed out that when N and T are in the same order of magnitude, the null of weak dependence of the CD test will be rejected even if the value of α is less than 1/2. In that case, the null of the CD test no longer remains a test for $\alpha < \frac{1}{2}$; rather, it turns into $\alpha < \frac{1}{4}$.

For the purpose of the study, the Pesaran (2015) CD test was applied to all the variables in the panel, and the Bailey et al. (2016) method was simultaneously used to estimate α for all the variables. This paper also applied the Baltagi et al. (2012) bias-corrected scaled LM test (CDLM$_{BCS}$) to examine the presence of CSD in the individual variables of log real dividends and share price. The CDLM$_{BCS}$ statistic tests the null hypothesis of no cross-section dependence against the alternative of the presence of cross-section dependence. The above tests were also applied to the residuals obtained from long-run dynamic estimators. The same is discussed in Section 3.3 of the paper.

Like CSD, the assumption of slope homogeneity in long-run regressions may lead to inconsistent and misleading estimates when the slope varies across panels. The assumption of slope homogeneity in panel long-run estimators may lead to heterogeneity bias when the long-run slope estimates vary across individual panels. A detailed discussion regarding the issue of heterogeneity is provided by various authors, such as Pesaran and Smith (1995); Pedroni (2019); Baltagi and Pesaran (2007), etc. Therefore, the Chudik and Pesaran (2015) dynamic CCEMG estimator was applied in this study that allow for long-run slope heterogeneity.

3.2. Panel Unit Root Test and Cointegration

Considering the effect of CSD, first-generation panel unit root and cointegration tests such as the Levin, Lin, and Chu Test or LLC Test (Levin et al. 2002), Im, Pesaran and Shin Test or IPS Test (Im et al. 2003), and Pedroni (1999, 2004) residual-based cointegration test, which assumes cross-sectional independence, had restrictive applications to the panel exhibiting cross-section dependence of error.[5] Consequently, second-generation tests were developed to allow for the presence of CSD while testing for panel unit root and cointegration. The two most common second-generation panel unit root and cointegration tests applied in most cointegration studies are the Pesaran (2007) cross-sectional augmented IPS test or the CIPS test and the Westerlund (2007) error-correction-based cointegration test.

Im et al. (1995) explained in their paper that one way of lowering the effect of cross-section dependence on the conventional panel unit root test is by subtracting the cross-sectional mean from the series and applying the panel unit root test to the demeaned series. Additionally, Pedroni (1999) demonstrated the technique of cross-sectionally demeaning the panel time series using time dummies.

As noted in Pesaran (2007), with the presence of the pairwise cross-section covariance of error structure, demeaning may not be very effective in eliminating the effects of CSD. Consequently, Pesaran (2007) developed a CIPS test or cross-sectional IPS test, which is obtained from the averaging of the cross-sectional augmented ADF statistics, better known as $CADF_i$. The $CADF_i$ is calculated from the OLS regression performed on individual panels augmented with the cross-sectional averages of lagged levels and first differences of the variables. The cross-sectional average is added in the regression as a representation of an unobserved common factor. According to Pesaran (2007), the CIPS test statistic is

a modified version of IPS t-bar test statistic and $CADF_i$ is the t ratio statistics calculated using the OLS estimates obtained from the cross-section regressions. The CIPS statistic tests for the null hypothesis of the presence of the unit root for all panels, vs. the alternative of some panels being stationary. Hence, rejecting the null would indicate that at least one panel in the data is stationary.

Therefore, the CIPS test statistic can be written as:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i$$

Pesaran (2007) also provided a truncated CIPS test statistic for a panel with a smaller time dimension.

Along with Pesaran's (2007) test, the Maddala and Wu (1999) Fisher-type ADF panel unit root test was applied to log real share price and dividends. Based on the comparative study conducted by Maddala and Wu (1999), the Fisher-type tests dominate the LLC or the IPS test in terms of size and power in the presence of the cross-correlation of errors. Hence, the Maddala and Wu (1999) Fisher-type ADF test was chosen over the IPS test. Like Pesaran (2007), the Maddala and Wu (1999) Fisher-type ADF test statistic evaluates the null of unit root in all panels vs. an alternative where at least one panel is stationary. Like the LLC and IPS tests, the Maddala and Wu (1999) Fisher-type ADF test assumes cross-section independence of error. Therefore, we applied the same time demeaned log real dividend and share price to counteract some effects of the presence of cross-section dependency.

In the context of testing for the presence of common stochastic trends or cointegration, Westerlund (2007) developed an error-correction-based panel cointegration test with four test statistics: two panel test statistics (P_τ and P_α) and two group mean statistics (G_τ and G_α).

Westerlund (2007) mentioned that unlike the residual-based test of cointegration developed by Pedroni (1999, 2004), the error-correction-based test is not based on any common factor restriction. To take account of the effects of CSD, the Westerlund (2007) ECM-based test allows for the bootstrapping technique of test statistics to generate a robust *p*-value.

Following the mathematical expression of the error-correction model used in the paper by Persyn and Westerlund (2008), the ECM-based conditional model used in this study can be written as:

$$\Delta sp_{it} = \delta_i' d_t + \alpha_i \left(sp_{i,t-1} - \beta_i' div_{i,t-1} \right) + \sum_{j=i}^{p_i} \alpha_{1ij} \Delta sp_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta div_{i,t-j} + \varepsilon_{it} \quad (5)$$

With sp_{it} representing the log real share price, div_{it} being the log real dividends, α_i term being the error-correction term and $\delta_i' d_t$ is either a deterministic constant or trend or both. Therefore, the test for the null of no cointegration is testing for the null of no error correction present between the regressor (div_{it}) and the dependent variable (sp_{it}). Hence, the null hypothesis is given as: $H_o : \alpha_i = 0$ for *all panels* with the homogenous alternative of $H_a : \alpha_i = \alpha < 0$ *for all panels* in the case of panel statistics, with a heterogenous alterative of $H_a : \alpha_i = \alpha < 0$ *for some panels* in the case of group mean statistics. The Westerlund (2007) ECM-based test allows for heterogeneity in short-run dynamics, an individual specific constant, and a trend term with weakly exogeneous regressors.[6]

Since the Westerlund (2007) test allows for weakly exogenous regressors, one approach to testing for weakly exogenous regressors was presented in the works of Demetriades and James (2011) and Herzer and Donaubauer (2018). Here, the authors used the Westerlund (2007) ECM-based model to run a reverse regression with the left-hand side variable as the regressor. In this paper, the weak exogeneity of the dividend series was tested by taking the div_{it} as the dependent variable in Equation (6).

$$\Delta div_{it} = \delta_i' d_t + \alpha_i \left(div_{i,t-1} - \beta_i' sp_{i,t-1} \right) + \sum_{j=i}^{p_i} \alpha_{1ij} \Delta div_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta sp_{i,t-j} + \varepsilon_{it} \quad (6)$$

Therefore, if the null hypothesis of $\alpha_i = 0$ is not rejected, we can assume the log real dividend series is weakly exogenous.

For a more detailed examination of the presence of cointegration between stock price and dividends, this paper also applied the Pedroni (1999, 2004) residual-based cointegration test on the selected sample data in conjunction with the ECM-based cointegration test.

Pedroni (1999, 2004) developed seven residual-based test statistics, where the first four statistics are the within dimension (panel) statistics, specifically, *panel v*, *panel ρ*, *panel t and panel ADF* and the following three statistics are between dimension (group mean) statistics: *group ρ*, *group t and group ADF*. Like the Westerlund (2007) ECM-based test, all seven statistics test for the null of "no cointegration in all panels" with an alternative hypothesis of "all panels are cointegrated" for within dimension statistics and "some panels are cointegrated" for between dimension statistics. The Pedroni (1999, 2004) cointegration test allows for heterogenous long-run and short-run coefficients with multiple regressors, individual constant and trend terms, and endogenous regressors. Although Pedroni's test assumes cross-sectional independence of the error term, it allows for time dummies to deal with the presence of CSD.

In addition to Pedroni's (1999, 2004) residual-based cointegration test, the Kao (1999) residual-based cointegration test was used in this paper. The residual-based cointegration test developed by Kao (1999) computes Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF) test statistics to test the null hypothesis of no cointegration. Kao's (1999) test allows for a homogenous cointegrating vector with heterogenous intercepts. Both Pedroni's (1999, 2004) and Kao's (1999) residual-based cointegration tests were applied to the time-demeaned log real dividend and share price.

3.3. Estimation of Long-Run Relationship

Estimating the long-run relationship in the presence of cross-sectional dependence and slope heterogeneity has its own challenges. Assuming homogeneity of the long-run cointegrating vector when it depicts heterogeneity may lead to serious errors and biases. The same goes for the cross-sectional dependence of error structure.

In their paper, Pesaran and Smith (1995) provide a detailed evaluation of the problems associated with assuming slope homogeneity when the slope coefficients are heterogeneous across panels, especially in dynamic panel data models, which may lead to inconsistent estimates. In return, they developed a mean group (MG) estimator that adopts the strategy of obtaining individual coefficients from each individual regression, and these are averaged across cross-sections. Later, Pesaran et al. (1997, 1999) developed a pooled version of the MG estimator, which the authors called PMG, or pooled mean group estimator. It implies a homogeneity restriction on the long-run coefficient, allowing the short-run dynamics to vary across individual panels. The PMG estimator can be applied to the panel when the dynamics in the long run are assumed to be homogenous. However, both the PMG and MG estimators assume the error term to be independent across the panel. The problems associated with assuming cross-sectional independence when the error terms are cross-correlated are already discussed in Section 3.1 of this paper.

In the context of cross-sectional dependence of error terms, Pesaran (2006) extended the mean group (MG) estimator of Pesaran and Smith (1995) by augmenting the cross-sectional averages of regressors to ease the effect of unobserved common factors while estimating long-run relationships for large N and T panels, which the author called the common cross effects mean group estimator or CCEMG estimator. Pesaran (2006) also developed a pooled version of the CCEMG estimator, known as the common-correlated effects pooled estimator or CCEP estimator. Nonetheless, the CCEMG/CCEP estimator assumes the regressors in the model to be strictly exogenous.

Chudik and Pesaran (2015) further extend the Pesaran (2006) CCEMG estimator into a dynamic model, allowing for weakly exogenous regressors and lagged dependent variables. The CCEMG estimator in a dynamic panel setting is meant for large panels with large N and T. Therefore, applying the CCEMG estimator to a small-sample panel time series

could lead to small-sample time-series bias. Chudik and Pesaran (2015) recommended the use of either a half-panel jackknife or recursive mean bias-correction techniques applied to the estimator. Chudik and Pesaran (2015) also suggested that the Pesaran (2006) CCEMG estimator with a weakly exogenous regressor under a dynamic panel approach can perform even better by including, $p = T^{1/3}$ additional lags of cross-sectional averages of the variables.

Taking all the above econometric challenges into consideration, Eberhardt and Presbitero (2015) used the error-correction representation of a dynamic CCEMG estimator with weakly exogenous regressors to investigate the linear dynamic link between public debt and growth while accounting for cross-country heterogeneity and cross-sectional dependency. Under the assumption of slope heterogeneity across individual firms and considering the presence of cross-sectional dependency due to any unobserved common factors, this paper has used their model to analyze the long-run linear relationship between log real share price and log real dividends.

Following the expression of error-correction representation of the dynamic CCEMG estimator presented in the Eberhardt and Presbitero (2015) paper, the estimation model used in this study is represented as:

$$\Delta sp_{it} = b_{0i} + b_{1i}^{EC} sp_{i,t-1} + b_{2i}^{D} div_{i,t-1} + b_{3i}^{d} \Delta div_{it} + b_{4i}^{CSA} \overline{sp_{t-1}} + b_{5i}^{CSA} \overline{div_{t-1}} +$$
$$b_{6i}^{CSA} \Delta \overline{sp}_t + b_{7i}^{CSA} \Delta \overline{div}_t + \sum_{l=1}^{p} b_{5il}^{CSA} \Delta \overline{sp}_{t-l} + \sum_{l=1}^{p} b_{6il}^{CSA} \Delta \overline{div}_{t-l} + \varepsilon_{it} \tag{7}$$

The above Equation (7) is the re-parameterized version of the dynamic CCEMG model with an error-correction term mentioned in the Eberhardt and Presbitero (2015) paper, where b_{1i}^{EC} is the coefficient of the error-correction term, and the long-run coefficient (β_i) can be generated from the error-correction term with the expression $(-b_{2i}^{D}/b_{1i}^{EC})$. The b_i^d is the coefficient of the short-run equation on the right-hand side of the main equation, which measures the short-run effect of log real dividends on log real share price. $b_{4i}^{CSA} \overline{sp_{t-1}}$, $b_{5i}^{CSA} \overline{div_{t-1}}$, $b_{6i}^{CSA} \Delta \overline{sp}_t$ and $b_{7i}^{CSA} \Delta \overline{div}_t$ are the augmented cross-sectional averages of all the variables used as additional regressors. $\sum_{l=1}^{p} b_{5il}^{CSA} \Delta \overline{sp}_{t-l}$ and $\sum_{l=1}^{p} b_{6il}^{CSA} \Delta \overline{div}_{t-l}$ are the additional lags of cross-sectional averages.

As pointed out by Eberhardt and Presbitero (2015), Equation (7) represents the Pesaran and Smith (1995) MG estimator, when not augmented with the cross-sectional averages of all the variables, and the Pesaran (2006) CCEMG estimator, when augmented with the cross-sectional averages of all the variables. One of the few advantages of using such an approach is that, along with estimating the long-run coefficient, it will provide an overall picture of the speed of adjustment at which the log real share price adjusts to any change in log real dividends in the long run.

The decision regarding the inclusion of a maximum number of additional lags of cross-section averages in a dynamic CCEMG is based on the standard rule of $p = T^{1/3}$ provided in Chudik and Pesaran (2015). This study has included up to three additional lags of cross-section averages and reported the result with one, two, or three additional lags of CSA. The residuals obtained from all the models with additional CSA lags were checked for the presence of strong and weak cross-sectional dependence. Finally, the Bailey et al. (2016) and Pesaran (2015) CD tests were applied to estimate the degree of cross-section dependence and to check for the presence of weak cross-section dependence among residuals after de-factoring with additional lags of cross-section average. The Baltagi et al. (2012) bias-corrected scaled LM test (CDLM$_{BCS}$) was also applied to the residuals obtained from the above-mentioned estimators to examine the presence of CSD. A recursive mean small-sample time-series bias-correction method was also applied to account for small time-series bias.

4. Data and Empirical Results

4.1. Data

The dataset used in this study consists of annual dividends per equity share paid by non-financial Indian firms. The period of study was selected as 1990–2017. All firms selected for the study were listed on the Bombay Stock Exchange (BSE). To avoid gaps and missing observations, only those firms paying dividends consistently between the fiscal years of 1990–2017 were selected. Since there was a significant cut in dividend payment by Indian firms from 2018 onwards (see Agrawal 2021), the number of years incorporated in this study was limited to 28 years, i.e., from the fiscal year of 1990 to the fiscal year of 2017. This helped in maintaining a healthy number of firms without compromising on the number of observations. In total, 60 non-financial firms were selected for our study. All data were collected from CMIE's Prowess DX database. Following in the footsteps of Campbell and Shiller (1987) and Froot and Obstfeld (1991), share price data for all 60 Indian firms were obtained for the beginning of the year. Since the observations were included for the fiscal year, the average share price was calculated for the month of April. The nominal values of the variables were then deflated using the wholesale price index (WPI) prevailing between the years 1990–2017, and their natural logarithmic values were calculated. To generate real share price value, we applied the WPI for the month of April. The dividend series for 60 Indian firms was deflated using the annual average wholesale price index.

4.2. Empirical Results and Discussion

4.2.1. Cross-Section Dependence Test

Table 1 reports the Pesaran (2015) weak cross-sectional dependence (CD) test statistics for both the variables along with their corresponding *p*-values. Along with that, Table 1 appends the Bailey et al. (2016) bias-corrected $\hat{\alpha}$ value or exponent of cross-section dependence for both the variables with the 95% confidence interval. Table 1 outlines the presence of weak and strong cross-section dependence in all variables.

Table 1. Pesaran (2015) CD test and Bailey et al. (2016) bias-corrected exponent of cross-section dependence.

	CD	**p Value**	$\hat{\alpha}_{0.05}$	$\hat{\alpha}$	$\hat{\alpha}_{0.95}$
sp_{it}	78.49	0.00	0.86	0.95	1.03
div_{it}	32.55	0.00	0.79	0.85	0.91

Note: Ditzen (2018, 2019, 2021) xtcd2 and xtcse2 Stata command was used to apply both the Pesaran (2015) CD test and estimate the Bailey et al. (2016) bias-corrected exponent of cross-section dependence.

From the results reported in Table 1, the Pesaran (2015) CD test rejects the null hypothesis of weak dependence for all the variables at a 1% level of significance. The bias-corrected $\hat{\alpha}$ value for the both the variables is >1/2 and its 95% confidence intervals for log real share price and log real dividend are [0.86, 1.03] and [0.79, 0.91], respectively. Therefore, the test result indicates the presence of strong cross-section dependence among variables across the panel. The presence of strong cross-section dependence could be due to any unobserved common factors such as bubbles, as was explained in the paper by Goddard et al. (2008).

Table 2 reports the results of the Baltagi et al. (2012) bias-corrected scaled LM test (CDLM$_{BCS}$). The CDLM$_{BCS}$ test statistic rejects the null hypothesis of no cross-section dependence for both the variables of log real dividends and share price. Hence, the result provides a clear picture of the presence of cross-section dependence in all the individual variables.

Table 2. Baltagi et al. (2012) bias-corrected scaled LM test of cross-section dependence.

	CDLM$_{BCS}$	p Value
sp_{it}	197.24	0.00
div_{it}	156.75	0.00

Note: Baltagi et al. (2012) bias-corrected scaled LM test statistic was calculated using the built-in command in EVIEWS 12.

4.2.2. Panel Unit Root Test

Tables 3 and 4 show the results of the Maddala and Wu (1999) Fisher-type ADF test and the Pesaran (2007) CIPS panel unit root test, respectively. The first-generation panel unit root test implies cross-sectional independence, as indicated in Section 3.2 of this paper. As a result, before conducting the Maddala and Wu (1999) Fisher-type ADF test, the data were demeaned and the test was conducted using lag orders of *P = 0, 1, 2,* and *3*, considering the presence of a deterministic trend and constant. The reason behind using time-demeaned log real share price and log real dividends was explained in Section 3.2 of this paper. In the case of log real dividends, Maddala and Wu's (1999) chi-squared test presented in Table 3, fails to reject the null of the presence of unit root in all panels at lag values of 2 and 3 at the 10% level of significance. The results did not change when the test was applied in the presence of only a constant. At lag values of 2 and 3, the test statistic was unable to reject the null at a 10% level of significance in the case of log real share price. The test result remained the same when only a deterministic constant was present. However, the Maddala and Wu (1999) test statistic rejects the null hypothesis of unit root when it was applied to the first difference of log real share price and dividends at all lag orders. Therefore, the Maddala and Wu (1999) Fisher-type ADF test results reflect that the variables are nonstationary at the higher lag orders.

Table 3. Maddala and Wu (1999) Panel Unit Root test (MW).

At level	*P = 0*	*P = 1*	*P = 2*	*P = 3*
	Deterministic: Constant with trend (Case I)			
sp_{it}	130.378 (0.244)	189.677 (0.000)	130.059 (0.250)	131.977 (0.214)
div_{it}	249.704 (0.000)	174.359 (0.001)	121.641 (0.441)	115.164 (0.608)
	Deterministic: Constant (Case II)			
sp_{it}	148.215 (0.041)	148.110 (0.042)	124.985 (0.359)	126.119 (0.333)
div_{it}	225.050 (0.000)	164.825 (0.004)	131.123 (0.230)	119.527 (0.495)
At first difference	*P = 0*	*P = 1*	*P = 2*	*P = 3*
	Deterministic: Constant			
Δsp_{it}	1529.373 (0.000)	790.909 (0.000)	445.633 (0.000)	277.350 (0.000)
Δdiv_{it}	1882.844 (0.000)	975.561 (0.000)	509.621 (0.000)	370.012 (0.000)

Note: Here, time-demeaned variables were used to evaluate the presence of panel unit root. "Multipurt" Stata command developed by Dr. Markus Eberhardt was used to apply the Maddala and Wu (1999) Fisher-type ADF test. The *p*-values for the relevant test statistics are indicated between parentheses.

Like the Maddala and Wu (1999) test results, the Pesaran (2007) CIPS test statistic specified in Table 4 in the context of log real dividends was unable to reject the null hypothesis of unit root in both the presence of a deterministic trend and a constant at a lag value of 2 and 3 at the 10% significance level. The results were the same in the presence of only a constant. However, in the case of the log real share price, the standardized CIPS test statistic fails to reject the null at a 10% level of significance around a deterministic trend and constant for all lag levels. It also fails to reject the null at a 5% and 10% level of significance around only a deterministic constant at lower lags of 0 and 1 and higher lags of 2 and 3, respectively. The Pesaran (2007) CIPS test reflects that the log real dividends are nonstationary at the higher lag orders and the log real share price is nonstationary at all lag orders.

Table 4. Pesaran (2007) second-generation CIPS test.

At level	P = 0	P = 1	P = 2	P = 3
	Deterministic: Constant with trend			
sp_{it}	1.305 (0.904)	0.516 (0.697)	1.285 (0.901)	1.045 (0.852)
div_{it}	−4.689 (0.000)	−1.796 (0.036)	2.527 (0.994)	3.704 (1.000)
	Deterministic: Constant			
sp_{it}	−1.360 (0.087)	−1.414 (0.079)	0.489 (0.687)	0.469 (0.681)
div_{it}	−5.316 (0.000)	−2.689 (0.004)	0.371 (0.645)	0.780 (0.782)
At first difference	P = 0	P = 1	P = 2	P = 3
	Deterministic: Constant			
Δsp_{it}	−24.652 (0.000)	−12.807 (0.000)	−5.980 (0.000)	−3.326 (0.000)
Δdiv_{it}	−29.419 (0.000)	−18.652 (0.000)	−8.303 (0.000)	−5.078 (0.000)

Note: The Stata command "Multipurt" develop by Dr. Markus Eberhardt was employed to conduct the above test. In this case since, the Pesaran (2007) test adjusts for the presence of CSD, the variables used were not time-demeaned. The *p*-values for the relevant test statistics are indicated between parentheses.

Next, assessing the results at the first difference of variables in both Tables 3 and 4, it can be presumed that the log real share price and dividend series are stationary at their first difference. Hence, this study proceeded with the panel cointegration tests.

With respect to the earlier literature, such as Nirmala et al. (2014), they also applied the Fisher-type ADF test developed by Maddala and Wu (1999) to the log real share price and dividends of Indian firms in the four key sectors of capital goods, healthcare, metal, and public sector undertaking. According to their findings, the log real share price and dividends tend to be I (1) stationary for all Indian firms in the four major sectors. Similarly, Goddard et al. (2008), Persson (2015) and Charteris and Chipunza (2020) applied the CIPS test to their log real share price and log real dividends using firm-level data. They observed the unit root in the log real share price and dividends of UK, Swedish, and South African companies, respectively. Therefore, our findings concur with the aforementioned empirical literature that confirms the I (1) stationarity of the log real share price and dividends.

4.2.3. Panel Cointegration Test

Tables 5 and 6 show the results of the Pedroni (1999, 2004) residual-based cointegration tests and the Westerlund (2007) error-correction-based cointegration tests, respectively. The cointegrating properties of both the variables were examined in the presence of only a deterministic constant with and without a deterministic trend. Just for convenience, Tables 5 and 6 were categorized into cases I and II, wherein case I includes both trend and constant term and case II includes only a constant term. As explained in Section 3.2, the Pedroni (1999, 2004) residual-based cointegration test was applied on the demeaned variables, i.e., including time dummies to nullify the effect of the cross-section dependence of error terms.

Table 5. Pedroni (1999, 2004) Residual-based cointegration test.

Dependent Variable: sp_{it}	Panel Statistics				Group Mean Statistics		
	ν	ρ	t	*ADF*	ρ	t	*ADF*
	Case I: Constant and Trends						
With time dummies	2.17	−12.84	−17.12	−13.96	−8.83	−17.33	−13.26
	Case II: Constant						
With time dummies	6.51	−10.95	−11.03	−9.20	−8.25	−11.80	−9.72

Note: xtpedroni user-written command developed by Neal (2014) was used in Stata to apply the Pedroni (1999, 2004) cointegration test. The AIC lag selection criteria along with maximum 2 ADF lags was used to select the lags for each individual panel. Panel statistic: H_o: No Cointegration in all panels; H_a: Cointegration in all panels. Group mean statistic: H_o: No Cointegration in all panels; H_a: Cointegration in some panels. The test statistics follow a normal distribution of N (0,1). The large negative (for ρ, t, and ADF) and positive value (only for panel ν) of test statistic will lead to the rejection of null hypothesis (see Pedroni 1999).

Table 6. Westerlund (2007) ECM-based cointegration test.

	t	Zt	p-value	Bootstrap p-value
	Dependent Variable: sp_{it} — Case I: Constant with Trend			
g_α	−2.956	−5.624	0.000	0.030
g_τ	−13.119	−1.262	0.104	0.100
p_α	−22.013	−6.461	0.000	0.010
p_τ	−12.280	−4.229	0.000	0.040
	Dependent Variable: sp_{it} — Case II: Constant			
g_α	−2.595	−7.048	0.000	0.000
g_τ	−11.251	−5.846	0.000	0.000
p_α	−18.914	−7.746	0.000	0.000
p_τ	−9.920	−9.928	0.000	0.000
	Dependent Variable: div_{it} — Case I: Constant with Trend			
	t	Zt	p-value	Bootstrap p-value
g_α	−2.375	−0.079	0.469	0.310
g_τ	−9.590	2.758	0.997	0.140
p_α	−17.030	−0.763	0.223	0.190
p_τ	−9.087	−0.195	0.423	0.050
	Dependent Variable: div_{it} — Case II: Constant			
g_α	−1.851	−0.632	0.264	0.170
g_τ	−6.847	0.420	0.663	0.070
p_α	−13.724	−2.526	0.006	0.110
p_τ	−6.336	−3.674	0.000	0.020

Note: Stata command xtwest developed by Persyn and Westerlund (2008) was used to apply the above test. Bootstrap p-values were obtained with 100 bootstrap replications. Only 1 lag value and 1 lead value were used to avoid loss of power due to overparameterization. (See Herzer and Donaubauer 2018).

Considering the results in Table 5, both the panel and group mean statistics of the Pedroni (1999, 2004) cointegration test reject the null of no cointegration in all panels at a 1% level of significance in both cases I and II. Therefore, the Pedroni (1999, 2004) residual-based cointegration test confirms the presence of cointegration between log real share price and dividends.

Table 6 represents the Westerlund (2007) error-correction-based cointegration panel and group mean statistics along with the corresponding asymptotic and bootstrap p-values. Since the bootstrap p-value is robust to the presence of cross-section dependence, the bootstrap p-values were considered for making conclusions about rejecting the null hypothesis under Westerlund (2007) ECM-based test statistics.

Looking at the bootstrap p-values for case I, the g_α, p_α and p_τ statistics reject the null hypothesis of no error correction or no cointegration at a 5% level of significance. However, the g_τ statistic fails to reject the null of no error correction or no cointegration at a 10% level of significance. For case II, g_τ no longer fails to reject the null of no cointegration at a 10% level of significance, and all the test statistics including g_τ are significant at a 1% level of significance.

The asymptotic p-values reveal that while all the test statistics, g_α, p_α, and p_τ, reject the null of no error correction or no cointegration at a 1% level of significance for both cases I and II, g_τ statistics fail to reject the null hypothesis at a 10% significance level for case I. However, they reject the null hypothesis at a significance level of 1% for case II.

Therefore, the Westerlund (2007) ECM-based test strongly suggests the presence of cointegration between log real share price and log real dividends when log real share price is taken as the dependent variable.

Table 6 also provides evidence in favor of the weak exogeneity of the dividend series. As discussed in Section 3.2, taking log real dividends as the dependent variable, for case I, the asymptotic *p*-values were unable to reject null of no error correction at a 10% level of significance for all the test statistics. The bootstrap *p*-values indicate the g_α, g_τ and p_α test statistics were unable to reject the null hypothesis at a 10% level of significance, while the p_τ statistic was unable to reject the null at a 5% level of significance. For case II, asymptotic *p*-values provide mixed results. The p_α and p_τ test statistics reject the null at a 1% level of significance, while the g_α and g_τ fail to reject the null of no error correction at a 10% level of significance. The bootstrap *p*-values for g_α and p_α statistics imply that the null was not rejected at a 10% level of significance, and for g_τ the null was not rejected at a 5% level of significance. As described in Section 3.2, if the null hypothesis of $\alpha_i = 0$ was not rejected, one can assume the weak exogeneity of dividend series. Considering the bootstrap *p*-values, since most of the Westerlund (2007) panel and group mean statistics were unable to reject the null of $\alpha_i = 0$, we can assume the log real dividend series is weakly exogenous. The weak exogeneity property of the dividend series might be further studied in future research to explore the reverse causality from share price to dividends.

Table 7 provides the results for Kao's (1999) residual-based cointegration test. The Kao (1999) DF and ADF test statistics reject the null hypothesis of no cointegration. As a result, all the panels confirm the presence of cointegration between share price and dividends.

Table 7. Kao (1999) Residual-based cointegration test.

Dependent Variable: sp_{it}	DF Statistics	*p*-Value	ADF Statistics	*p*-Value
With time dummies	−11.36	0.00	−3.55	0.00

Note: To apply Kao (1999) residual-based cointegration test, built-in Stata command xtcointtest was used. The AIC lag selection criteria along with maximum 2 ADF lags was used. The AR parameter was assumed to be same for all panels. DF and ADF statistic were tested for—H₀: No Cointegration; Hₐ: Cointegration in all panels.

The test results provide supporting evidence in favor of the validity of PVM and are consistent with the results obtained by the studies using firm-level data, such as Marsh and Power (1999), Nasseh and Strauss (2004), Goddard et al. (2008), Nirmala et al. (2014) Persson (2015) and Charteris and Chipunza (2020).

4.2.4. Long-Run Estimation Results

Based on the explanation provided in Section 3.3 of this paper regarding the application of the Chudik and Pesaran (2015) dynamic CCEMG estimation model with an error-correction term, Table 8 reports the result of the same with three, two and one additional lags of cross-sectional averages of variables in columns [1], [2] and [3], respectively. Along with that, the results from the Pesaran (2006) CCEMG estimator were presented in column [4], and the pooled version of the CCE (CCEP) estimator in column [5] is recommended by the same author. Additionally, the two standard estimators—Pesaran et al. (1997, 1999), the pooled mean group (PMG), and Pesaran and Smith (1995), the mean group (MG)—were included in the result table in columns [6] and [7].

Despite being aware of the main shortcomings of CCEMG, CCEP, MG, and PMG estimators with regards to this study (as it was addressed in Section 3.3), these estimators were still used to understand how the long-run coefficient behaves when alternative estimators are applied. Table 8 also reports the cross-section dependence test results applied to the residuals obtained from the cointegration or long-run regressions in columns [1]–[7].

Looking at the results in columns [1] [2] and [3] of Table 8, the dynamic CCEMG estimator provides long-run coefficients of 1.00, 0.93, and 0.97, respectively. All the long-run coefficients (LR Coefficient) mentioned are highly significant at the 1% level of significance. Very similar results were obtained by applying the CCEMG and CCEP estimators. The result of long-run estimates close to unity indicates the presence of a strong long-run relationship between the log real share price and dividends of Indian firms. PMG and MG

estimator results in columns [6] and [7], of 0.90 and 0.96, respectively, are comparable to the results provided by Nasseh and Strauss (2004). They applied PMG and MG estimators applied to a panel of S&P100 indexed US stocks. They also demonstrated the presence of a strong long-run relationship between log real share price and dividends with their PMG and MG estimators, providing estimates close to unity.

Table 8. Long-run panel estimation.

	DCCEMG	DCCEMG	DCCEMG	CCEMG	CCEP	PMG	MG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Dependent variable: sp_{it}							
LR Coefficient	1.00	0.93	0.97	1.01	0.92	0.90	0.96
ECT (-)	0.62	0.60	0.56	0.55	0.44	0.53	0.64
Additional CSA Lags	3	2	1	0	0	0	0
α	0.23	0.23	0.13	0.55	0.57	0.87	0.87
CI 95%	[0.13 0.33]	[0.16 0.30]	[0.03 0.24]	[0.59 0.63]	[0.60 0.65]	[0.90 0.91]	[0.85 0.90]
CD	−1.57	−2.01	−1.88	−2.08	−3.20	127.05	124.55
p-value	0.12	0.05	0.06	0.04	0.001	0	0
CDLM$_{BCS}$	36.40	30.25	23.31	18.13	22.57	262.89	247.49
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	60	60	60	60	60	60	60
RMSE	0.35	0.36	0.36	0.36	0.40	0.64	0.61
Adjusted R Squared	0.79	0.78	0.79	0.79	−0.06	0.6	0.38

Note: XTDCCE2 Stata command developed by Ditzen (2018, 2019, 2021) was used to estimate the long-run coefficients (LR Coefficient) for all columns. XTCSE2 and XTCD2, developed by the same author, were used to check for strong and weak cross-section dependence among residuals. For calculating CSD using Baltagi et al. (2012) CDLM$_{BCS}$ test statistics among residuals, the built-in command in EVIEWS 12 was used. Eberhardt and Presbitero (2015) used the XTMG Stata command developed by Dr. Markus Eberhardt to estimate the long-run coefficients and error-correction terms in their paper. Even though this paper used the XTDCCE2 Stata command, the codes used to estimate the above long-run coefficients and error-correction terms were replicated using the codes shared by Dr. Markus Eberhardt on his website (https://sites.google.com/site/medevecon/research-by-topic accessed on 1 June 2020).

The CD test result obtained from the cointegrating regressions in column [1] was unable to reject the null hypothesis of a weak dependence of errors. Column [2] and [3] also failed to reject the null at a 5% level of significance. Table 8 also presents the result of the bias-corrected estimate of the exponent α for first three columns with the value of $\alpha < \frac{1}{2}$, which suggests that the correlation of residuals across individual firms is weak. The 95% confidence interval (CI 95%) of the bias-corrected estimate α lies in the range of $0 \leq \alpha \leq \frac{1}{2}$, which provides evidence in favor of the dependence of error across individual firms' being weak rather than strong. However, the CD test results and the bias-corrected α value in Table 8 demonstrate the presence of strong cross-section dependence among residuals obtained from CCEMG CCEP, PMG and MG estimators. This implies that the inclusion of additional lags of cross-section averages of variables in the dynamic CCEMG estimators mentioned in columns [1]–[3] aided in weakening the effect of strong unobserved common factors.

The result from the application of CDLM$_{BCS}$ test to the residuals obtained from the long-run dynamic estimators in columns [1]–[7] of Table 8, however, rejects the null hypothesis of no cross-section dependence. Baltagi et al. (2012) have explained the applicability of the test only to fixed effect homogenous panel data models and have cited the non-robustness of the test towards the heterogeneous panel data model. This could be possibly a reason, that the CDLM$_{BCS}$ test statistic rejected the null hypothesis of the no cross-section dependence among the residuals obtained for the estimators in columns [1]–[7], while the Pesaran (2015) CD test failed to do the same. However, the overall result from the application of Pesaran's (2015) CD test in Table 8 implies the inclusion of additional lags of cross-section averages of variables in the dynamic CCEMG estimators mentioned in columns [1]–[3] aided in weakening the effect of strong unobserved common factors.

The coefficient of the error-correction term (ECT) for all the columns in Table 8 is negative and significant at a 1% level of significance, which provides convincing evidence for the presence of long-run causality running from log real dividends to log real share price, which in turn favors the presence of a long-run equilibrium between the two variables.

5. Conclusions

This paper explored the relevance of the Campbell and Shiller (1988) log-linearized present value model by analyzing the long-run relationship between share price and dividends of selected dividend-paying Indian firms. As a preliminary examination of the log-linearized present value model, first a series of first-generation and second-generation panel unit root and cointegration tests was employed in this study to check for cointegration between log real share price and dividends. Then, the presence of a long-run equilibrium relationship between the variables was examined by estimating the long-run coefficients using a reparametrized version of the dynamic CCEMG estimator of Chudik and Pesaran (2015), augmented with additional CSA lags and error-correction terms. This novel method of estimating long-run relations was used in the paper of Eberhardt and Presbitero (2015). To overcome the issues associated with time-series or aggregate data, firm-level data over time-series data were considered for this study. The dataset used in this study contained share prices and dividends of 60 BSE listed Indian firms paying continuous dividends for an annual time series of 28 years (1990–2017). All the methodology related to panel time-series data that was employed in this paper was robust to the presence of cross-section dependence of errors and slope heterogeneity. To examine the robustness of the long-run estimators to the presence of strong cross-section dependence of residuals, the Pesaran (2015) weak cross-section dependence test and the bias-correction estimate α developed by Bailey et al. (2016) were applied to the residuals obtained from the long-run estimators. The result suggests that the applied long-run estimator of Chudik and Pesaran (2015) is potent in the presence of strong cross-section dependence of residuals, thus producing consistent estimates.

The findings of this study corroborate those of other studies that used firm-level data to validate the log-linearized present value model (see Marsh and Power 1999; Nasseh and Strauss 2004; Goddard et al. 2008; Nirmala et al. 2014; Persson 2015; and Charteris and Chipunza 2020). The study provides evidence that log real dividends and the log real share price are cointegrated, and the results validate the presence of a long-run equilibrium relationship between both the variables across a panel of 60 Indian firms with the presence of significant long-run coefficients and an error-correction term.

This helps to articulate the results of the study to practitioners and academicians by explaining the dividends as a function of share price in the context of Indian firms. Hence, a better understanding of the share price fluctuation could put forth a better understanding of the seeming rationality/irrationality of the Indian stock market. The validity of PVM in the context of Indian markets could equip Indian firms with better and more realistic dividend policies that could be useful in enhancing their market valuation in the long term. However, the findings of this study are not an end in themselves. The results, especially the behavioral functioning of both dividends and share price with respect to the Indian stock markets, could be further examined in light of other fundamental variables that could have a potential impact on the share price using both aggregate and firm-level data, and more advanced panel econometric techniques that account for the presence of structural breaks and nonlinearity in dividend and share price series could be used to explain their relationship better both in the long and short term.

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Notes

1 For a detailed explanation on the mathematical expression of present value relation used in Equations (1)–(4), please refer Chapter 7 of Campbell et al. (1997). Additionally, see Goddard et al. (2008); McMillan (2010).

2 For example, Goddard et al. (2008) have cited the importance of controlling for CSD before testing the cointegration between share price and dividend as an exercise to reduce the effect arising from non-fundamental factors such as bubbles.

3 O'Connell (1998); Maddala and Wu (1999) have explained the effect of CSD on the conventional panel unit root test assuming cross-section independence. Breitung and Pesaran (2008) have provided a brief outline of the effect of cross-section dependence. Phillips and Sul (2003) have discussed the effect of the presence of CSD on conventional panel estimators. Westerlund (2007) has presented the importance of controlling for CSD in panel cointegration tests.

4 The basic concept and definition of weak vs. strong dependence of error structure are provided in the papers by Chudik et al. (2011); Pesaran (2015); Bailey et al. (2015, 2016).

5 For details regarding the above first-generation tests, see Levin et al. (2002); Im et al. (2003); Pedroni (1999, 2004).

6 More information on the ECM-based cointegration test may be found in the papers Westerlund (2007); Persyn and Westerlund (2008).

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