Journal of Finance and Economics
Volume 3, Issue 3 (2015), 38-45
ISSN 2291-4951 E-ISSN 2291-496X
Published by Science and Education Centre of North America

Has the Stock Market Become More Efficient in the Long-Run? Evidence from U.S Corporations

Kai Chen[1], Jie Feng[2], & Richard D. Marcus[3*]

[1] School of Economics & Business, SUNY Oneonta, Oneonta, NY 13820; Email: kchenwx815@gmail.com

[2] School of Economics & Business, SUNY Oneonta, Oneonta, NY 13820; Email: jie.feng@oneonta.edu

[3] Lubar School of Business, University of Wisconsin-Milwaukee, USA

*Correspondence: Richard D. Marcus, Lubar Hall S430F, 3202 N Maryland Ave, Milwaukee WI, 53217, USA. Tel: 414-229-4103; Email: marcus@uwm.edu

DOI: 10.12735/jfe.v3i3p38 URL: http://dx.doi.org/10.12735/jfe.v3i3p38

Abstract

Using the cointegration model to deal with nonstationary time series, we estimate the long-run relationship between the average stock price and the average dividend. The results from U.S. time series data of 141 years show that the discount rate is lower in the second half of this period, which indicates that stock market becomes more efficient and capital cost becomes lower in the long run. Along with well-documented narrowing of the bid-ask spreads of stocks over time and the growing speed of stock market order fulfillment, market efficiency is further exemplified by lower dividend yields.

JEL Classification: G10, C58

Keywords: cointegration, discount rate, market efficiency

1. Introduction

Discount rate appears in the present value model:

$$PV = \sum_{i=1}^{\infty} \frac{c_i}{(1+r)^i} \tag{1}$$

where PV is present value, c_i is the dividend payment in time i, and r is discount rate. The intrinsic value of a firm's stock is defined as the sum of the present values of all cash payments, *i.e.*, the future cash payments discounted at the appropriate risk-adjusted rate of return, r. Here, r is associated with the risk of a stock. The higher risk a firm is taking, the higher will be the appropriate discount rate used in the present value model. Generally, investors would take on higher risk if there was more asymmetric information between investors and a firm.

Markets with more asymmetric information would be working less efficiently, as private information may not be fully incorporated into the current stock prices. In this sense, the average discount rate of all stocks in a market might reflect the overall efficiency of market. The discount rate also represents the return rate that investors demand from the firm based on their judgment of the risk of stock; it is why this rate is also called capital cost. In this sense, the average discount rate of all stocks might represent the opportunity cost of funds, influencing interest rate and many other important variables in economy. Thus, estimating the discount rate and understanding its long-run change is meaningful. If we suppose that a firm will pay a constant dividend d permanently in future, the present value model could be written as $PV = \frac{d}{r}$. To wit, if the market price of a stock reflects its true value and if the firm's dividend is expected to be stable, then r, the discount rate, can be solved or discovered. In light of this model, we can say that a stock price should have a long-run relationship with its current dividend, even though both the stock price and the dividend would fluctuate over time.

Using the long run time series data of the average stock price (*Stock Price*) and the average dividend (*Dividend*) across all firms in a county, we can estimate the average discount rate for a county by running the regression model:

$$Stock\ Price_t = \alpha + \beta\ Dividend_t, \tag{2}$$

in which, the reciprocal of β should represent the discount rate, i.e., $r=1/\beta$.

Now the econometric problem we face is that these time series might be non-stationary processes. For instance, they could be random walks, trends, changing variances or covariances. If we apply OLS regression to the models above, the estimators are not normally distributed, leaving us inconsistent estimation of parameters. Results extracted from non-stationary time series may be spurious in that they may lead to a relationship between two variables where the relationship does not exist.

The usual approach to this problem is to difference the series. If a test fails to reject the hypothesis of non-stationarity of our variables, we can difference the series in question before using them in our regressions. While this is acceptable, differencing may result in a loss of information about the long-run relationship between two variables.

Cointegration analysis, developed by Engle and Granger (1987), solves this problem. Sometimes two variables are non-stationary but a linear combination of those variables is stationary. If this is the case, we say that these two variables are cointegrated. We can establish a regression model of these two variables and estimate this model using OLS. Engle and Granger prove that OLS provides consistent estimates of parameters, if cointegration of two variables exists. Furthermore, the residuals of this regression then can be used to test whether these two variables are indeed cointegrated.

In this paper, we apply the cointegration analysis to estimate the discount rate in the United States. We first estimate over a full sample period from 1871 to 2012, and then estimate over two sub-sample periods, 1871-1945 and 1946-2012, respectively. Our primary objective is to compare the discount rates between these two time periods. The long-run change in the discount rate can tell us how the U.S. stock market has been changing in terms of market efficiency and capital cost. The conventional study on the market efficiency hypothesis focuses on whether stock markets are of weak, semi-strong, or strong form efficiency. The empirical evidence has been mixed (Fama, 1970 & 1998; Malkiel, 2003). This study contributes to the market efficiency literature by looking at whether a stock market becomes more efficient in a long-run in terms of a measure of market information asymmetry—the average discount rate for all firms in the market. Our results are easily stated; the discount rate is lower in the latter sub-sample period than in the former sub-sample period, indicating that the U.S. stock market has become more efficient and the capital cost has become lower.

The organization of the paper is as follows. Section 2 describes data used in our study. Section 3 describes the results of the empirical analysis. And Section 4 concludes.

2. Data

The data set used in our paper is the stock market data coming from Professor Robert J. Shiller's website. This data set contains monthly average stock price and dividend data of a broad stock index of the Standard and Poor's Portfolio, starting January 1871. The monthly dividend data before 1926 are from Cowles and associates (1939), interpolated from annual data, and the monthly dividend data since 1926 are computed from the S&P, with linear interpolation to monthly figures. Stock price data are monthly averages of daily closing prices. Using The CPI-U (Consumer Price Index-All Urban Consumers) published by the U.S. Bureau of Labor Statistics for post-1913 period and Warren and Pearson's price index for prior-1913 period, Professor Shiller computes the real term of the variables. Campbell and Shiller (1987) use the similar data set to estimate the discount rate in U.S. over a period from 1871 to 1987.

We use the data of these two variables from 1871 to 2012 to estimate the model. The term *Stock Price* represents the Standard and Poor's composite stock price index, and the term *Dividend* represents of the average dividend of the firms in the index, both in real term. To be consistent with Campbell and Shiller (1987) in terms of methodology, we convert them into yearly measures.

3. Empirical Analysis

The Engle-Granger cointegration test involves three steps. First, determine the orders of integration for each of the variables under consideration; that is, difference each series successively until stationary series emerge. Usually, one-order difference would be a stationary series. Second, estimate cointegration regressions with OLS using variables with the same order of integration. Finally, test for stationarity of residuals from cointegration regressions (see Engle & Granger, 1987; Miller, 1991). We develop our analysis in this order.

3.1 . Testing for Stationarity of Three Time-Series Variables: *Stock Price* and *Dividend*

We follow the methodology of Dickey and Fuller (1981) to test the stationarity of a time-series variable. Table 1 reports the results of the Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests for the stationarity of the two time-series variables— *Stock Price* and *Dividend*, respectively— as well as of their first-differences. For each test, we present four statistics: three *t*-statistics for zero mean, single mean, trend, and *F*-statistic. The three *t*-statistics for zero mean, single mean, and trend are computed based on the following regression models.

$$y_t = \alpha_1 y_{t-1} + e_t \tag{3}$$

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + e_t \tag{4}$$

$$y_t = \alpha_0 + \gamma t + \alpha_1 y_{t-1} + e_t \tag{5}$$

Let $\hat{\alpha}_1$ be the estimated regression coefficient for first lag of the series, and let $se_{\hat{\alpha}_1}$ be the standard error of $\hat{\alpha}_1$. The *t*-statistic is:

$$t = \frac{\hat{\alpha}_1 - 1}{se_{\hat{\alpha}_1}} \tag{6}$$

The *p*-values, calculated by SAS program based on the Dickey-Fuller test, are reported in parentheses below each *t*-statistic. We run a Dickey-Fuller unit root test on each variable series by estimating the unrestricted regression:

$$y_t - y_{t-1} = \alpha_0 + \gamma t + (\alpha_1 - 1) y_{t-1} + e_t \tag{7}$$

and the restricted regression:

$$y_t - y_{t-1} = \alpha_0 + e_t \tag{8}$$

We tested the restrictions by calculating an *F* ratio and comparing it to the critical values provided by Dickey and Fuller (1981, p.1063).

Augmented Dickey-Fuller tests are carried out by expanding the regressions above to include lagged changes $\sum_{j=1}^{4} \lambda_j \Delta y_{t-1}$ on the right-hand side of the equations. The *t*-statistics and *F*-statistic are calculated in the same way.

Table 1. Test for stationarity

This table shows the results of the test for stationarity of 2 time-series variables, *Stock Price* and *Dividend*, from 1871 to 2012. The term *Stock Price* represents the Standard and Poor's composite stock price index, and the term *Dividend* represents of the average dividend of the firms in the index, both in real term. Panel A shows the results of DF Test, and Panel B shows the results of ADF Test. The values in parentheses are *p*-value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dickey-Fuller Test								
Variable	Levels				1st-Difference			
	t-statistic for zero mean	*t*-statistic for single mean	*t*-statistic with trend	*F*-statistic	*t*-statistic for zero mean	*t*-statistic for single mean	*t*-statistic with trend	*F*-statistic
Stock Price	3.771 (0.99)	3.132 (0.99)	1.743 (0.99)	5.33	-6.551*** (<0.01)	-6.639*** (<0.01)	-6.794*** (<0.01)	23.32**
Dividend	1.210 (0.94)	-0.344 (0.91)	-2.338 (0.41)	3.01	-9.374*** (<0.01)	-9.479*** (<0.01)	-9.469*** (<0.01)	44.90**
Panel B: Augmented Dickey-Fuller Test								
Variable	Levels				1st-Difference			
	t-statistic for zero mean	*t*-statistic for single mean	*t*-statistic with trend	*F*-statistic	*t*-statistic for zero mean	*t*-statistic for single mean	*t*-statistic with trend	*F*-statistic
Stock Price	1.972 (0.98)	1.479 (0.99)	0.143 (0.99)	1.71	-4.145*** (<0.01)	-4.381*** (<0.01)	-4.807*** (<0.01)	11.68**
Dividend	1.324 (0.95)	-0.094 (0.94)	-2.373 (0.39)	3.28	-4.748*** (<0.01)	-4.999*** (<0.01)	-5.078*** (<0.01)	12.96**

The results shown in Table 1 are straightforward. In terms of levels, the *t*-statistics and *F*-statistic do not reject the null hypothesis of non-stationary for the time series *Stock Price* and *Dividend* in both DF and ADF tests. After first order differencing, the *t*-statistics in both DF and ADF test reject the null hypothesis of non-stationarity at the 1 percent level, and the *F*-statistic does so at the 5 percent level. The results of the stationarity indicate that using the level variables of *Stock Price* and *Dividend* in OLS regression might lead to inconsistent estimation of parameters. We have to apply the cointegration analysis to get the consistent estimation.

3.2 . Cointegration Analysis

After verifying the stationarity of first differences of *Stock Price*, and *Dividend*, we apply OLS to the model in the introduction. If cointegration exists between *Stock Price* and *Dividend*, we say that the OLS estimator is normally distributed and our estimations of parameters are consistent. We run the model and use Durbin-Watson and Dickey-Fuller methods to check their cointegration. We first run the model from 1871 to 2012 to check the cointegration over the full-sample period. The results are presented in Panel A, Table 2.

Table 2. Analysis of cointegration regressions

This table shows the results of the test for the cointegration between *Stock Price* and *Dividend*. Panel A reports the results for the full-sample period (1871-2012), and Panel B reports the results for a sub-sample period (1871-1987). The term *Stock Price* represents the Standard and Poor's composite stock price index, and the term *Dividend* represents of the average dividend of the firms in the index, both in real term. The errors from the cointegration models are recovered to perform the augmented Dickey-Fuller (ADF) non-stationarity tests based on the following regression:

$$d\mu_t = \sigma_1 \mu_{t-1} + \sum_{i=1}^{4} \sigma_{1=i} d\mu_{t-i} + e_t \tag{9}$$

where μ_t is the error from the cointegration equation, e_t is a stationary random error, and the null hypothesis of non-stationarity is rejected when σ_1 is significant negative. The Dickey-Fuller (DF) tests for non-stationarity delete the summation. $\overline{R}^2$ is the adjusted coefficient of determination and D-W is the Durbin-Watson statistic. The values in parentheses are *p*-value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Coefficients		$\overline{R}^2$	D-W	DF	ADF
	Intercept	Dividend				
Panel A: full-sample period (1871-2012)						
Stock Price	-118.205*** (<0.01)	50.859*** (<0.01)	0.699	0.235	1.125 (0.13)	-1.945** (0.04)
Panel B: sub-sample period (1871-1987)						
Stock Price	-12.729*** (<0.01)	30.783*** (<0.01)	0.858	0.431*	-3.656*** (<0.01)	-3.251*** (<0.01)

The results in Panel A show that the ADF test rejects the null hypothesis of non-stationary residual at the 5 percent level. But the DF test and D-W test do not reject the null hypothesis. So, we say that the cointegration exists under the ADF test at the level of 5%, but not under the D-W test and DF test. This result is not consist with the results of Campbell and Shiller (1987), who tested the cointegration between stock prices and dividends using data from 1871 to 1987 and PPI based on 1967. We repeated their test and got very similar results. The repeated test, reported in Panel B, Table 2, indicates that *Stock Price* and *Dividend* are cointegrated under all tests. Miller (1991) points out that the high $\overline{R}^2$ and low D-W statistics suggest possible spurious regression. Considering that $\overline{R}^2$ is not too high (0.699), D-W statistics is not too low (0.235), we conclude that there is weak evidence supporting the cointegration between *Stock Price* and *Dividend*.

To follow the change in discount rate over time, we follow Miller (1991) and split the sample period into two sub-sample periods at 1945 to estimate conintegration model respectively. In this way, we can test for the structural shifts and compare the estimated discount rates from two different time period. Panel A and B in Table 3 report the results of the cointegration regressions for the sub-sample periods 1871-1945 and 1946-2012, respectively.

Table 3. Analysis of cointegration regressions

This table shows the results of the test for the cointegration between *Stock Price* and *Dividend*. Panel A reports the results for the full-sample period (1871-1945, and Panel B reports the results for a sub-sample period (1946-2012). The term *Stock Price* represents the Standard and Poor's composite stock price index, and the term *Dividend* represents of the average dividend of the firms in the index, both in real term. The errors from the cointegration models are recovered to perform the augmented Dickey-Fuller (ADF) non-stationarity tests based on the following regression:

$$d\mu_t = \sigma_1 \mu_{t-1} + \sum_{i=1}^{4} \sigma_{1=i} d\mu_{t-i} + e_t \tag{10}$$

where μ_t is the error from the cointegration equation, e_t is a stationary random error, and the null hypothesis of non-stationarity is rejected when σ_1 is significant negative. The Dickey-Fuller (DF) tests for non-stationarity delete the summation. $\overline{R}^2$ is the adjusted coefficient of determination and D-W is the Durbin-Watson statistic. The values in parentheses are *p*-value. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Coefficients		$\overline{R}^2$	D-W	DF	ADF
	Intercept	Dividend				
Panel A: full-sample period (1871-1945)						
Stock Price	-2.597 (0.52)	20.420*** (<.001)	0.808	0.732**	-4.048*** (<.001)	-2.243** (0.02)
Panel B: sub-sample period (1946-2012)						
Stock Price	-337.379*** (<.001)	75.88*** (<.001)	0.716	0.443*	0.366* (0.08)	-1.511* (0.10)

It is not a surprise that the results in sub-sample period 1871-1945 are consistent with the results in sub-sample period 1871-1967, with all statistics suggesting cointegration. Comparing with the full sample, the D-W and DF do reject non-stationary error much more strongly. For the sub-sample period 1946-2012, the D-W, DF, and ADF tests support the cointegration only at 10% level. Furthermore, we can check the autocorrelation and partial-autocorrelation to corroborate our judgment. The autocorrelation and partial-autocorrelation charts resemble stationary error structures; the autocorrelation for the residual of Model 1 decline to zero quickly, while the partial-autocorrelation function has a spike of 0.82959 at lag one and a spike of –0.3579 at lag two only. The evidence supports that *Stock Price* is cointegrated with *Dividend* throughout the two sub-sample periods.

After verifying the conintegration, we can now look at the estimates of the coefficients of *Dividend* in OLS model. We can safely say that the estimates of the coefficients in the two sub-sample periods are consistent and can use the estimates to compute the discount rate in the two sub-sample periods. They are 1/20.42= 0.049 and 1/75.88=0.0132 in first and second periods, respectively. The decrease in the discount rate over more than one hundred years indicates that the stock market in the U.S. has a long trend of increasing the market efficiency and lowering the capital costs.

4. Conclusion

The discount rate contains a great deal of information. An average discount rate of all stocks in a market can tell market efficiency and opportunity cost. A long run discount rate can be estimated by regressing the stock price against the dividend. However, the problem of non-stationarity of time series variables might result in inconsistent estimation of the model. Application of the cointegration analysis enables us to deal with this problem. In this paper, we use the cointegration analysis to estimate the long run relationship between stock price and dividend over two periods, 1871-1945 and 1946-2012. We found that the discount rate lowered from 4.9% in the first period to 1.32% in the second period. This result indicates that the stock market in the U.S. States has become more efficient and capital cost has become lower in the long run. This evidence, along with the well- known decline in the bid-ask price (Corwin & Schultz, 2012) and the greater speed of stock market order execution (Hendershott & Moulton, 2011), bolsters the case of growing market efficiency in the long run.

References

[1] Campbell, J. Y., & Shiller, R. J. (1987). Cointegration and tests of present value models. *Journal of Political Economy*, *95*(5), 1062-1088.

[2] Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719-760.

[3] Cowles, A., & associates. (1939). *Common Stock Indexes* (2nd ed.). Bloomington, Ind.: Principia Press.

[4] Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*(4), 1057-1072.

[5] Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation and testing. *Econometrica*, *55*(2), 251-276.

[6] Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

[7] Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*. *49*(3), 283–306.

[8] Hendershott, T., & Moulton, P. C. (2011). Automation, speed, and stock market quality: The NYSE's hybrid. *Journal of Financial Markets*, *14*(4), 568-604.

[9] Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, *17*(1), 59-82.

[10] Miller, S. M. (1991). Monetary dynamics: An application of cointegration and error-correction modeling. *Journal of Money, Credit, and Banking, 23*(2), 139-154.

[11] Shiller, R. J. (n.d.). *Online data – Robert Shiller*. Retrieved from http://www.econ.yale.edu/~shiller/data.htm.

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal. This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution 4.0 International License.