Corruption and Stock Market Returns: Evidence from Panel Data Analysis

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We examine if corruption has any effect on stock market returns. Using balanced panel data that consist of cross-sectional groups and time periods, we find that an improvement in corruption has a positive effect on stock market returns, and time effects are more dominant than group effects. In addition, it is shown that the random time effect model is preferred to the fixed time effect model for the relationship between corruption and stock market returns. Our study is expected to provide not only a new insight to investors in terms of international diversification but also alternative options to socially responsible or ethical investment funds.

JEL classification: **G11; G15**
Keywords: Corruption; Stock market; Panel data; Fixed time effect; Random time effect

1. Introduction

Corruption exists almost everywhere around the world. If corruption flourishes in institutional systems through regulations, policies, or strategies, there is no doubt that some groups will obtain significant gains at the expense of others. The effect of corruption has been widely studied by economists as well as sociologists. According to Tanzi and Davoodi (1997) and Svensson (2005), corruption can occur in many different ways such as economic, political, cultural, legal, and even tax forms. In particular, much of the economic research focuses on investigating and analyzing corruption in terms of economic efficiency or corporate governance (Beck and Maher 1986; Davids 1999; Wu 2005; Halkos and Tzermeres 2010; Bishara 2011; Chen 2011; Caron, Ficici, and Richter 2012; Qerimi and Sergi 2012; Chakraborty 2015; Dzhumashev 2016). There are two opposite traditional viewpoints with regard to the effect of corruption. Typical studies that represent these different perspectives are Lui (1985) and Mauro (1995). While the former shows that corruption has a positive effect on economic efficiency by deriving the optimal bribing model for customers, the latter explains the negative effect of corruption by showing evidence that corruption weakens investment and economic growth.

Since corruption can be a serious issue in many countries and feed into various aspects in their financial markets, it is certainly a meaningful task to investigate the effect of corruption across international stock markets. Nevertheless, few studies delve into this area. Although Pellegrini and Pellegrini (2010) examine the relationship between corruption and stock returns, they use countries' overall corruption indices to explain individual companies' share returns rather than countries' entire stock market returns. Also, some studies attempt to investigate the effect of corruption on direct investments but they focus on entire investment cash flows between countries rather than stock market investments (Habib and Zurawicki 2002; Lambsdorff 2003; Egger and Winner 2005; Godninez and Garita 2016; Qian and Sandoval-Hernandez 2016). While traditional financial models do not take into account corruption as one of the factors that influence stock market returns, it must be worthwhile to study whether or not corruption has any effect on stock market returns. If a change in the level of corruption turns out to affect stock market returns across international stock markets, this provides a useful information to investors who vigorously seek alternative options to socially responsible or ethical investment funds in terms of international diversification. Since there is little research on this area, we are strongly motivated to investigate if corruption significantly influences stock market returns across global stock markets.

Several indices that represent corruption have been created. However, according to Paldam (2002) and Halkos and Tzermeres (2010), the Corruption Perception Index (CPI) developed by Transparency International (TI) is considered the best overall corruption index and ranks countries based on their CPI scores. We adopt the CPI for our study. Because Transparency International has published the CPI annually since 1995, our data are all annual. We construct balanced panel data that consist of cross-sectional groups (countries) and time series (years). With this panel data, we secure as much data as possible and identify group or time effects.

We find that an improvement in corruption tends to increase stock market returns. This finding is actually in line with the traditional viewpoint based on Mauro (1995). Our panel data analysis shows that the random time effect approach is preferred to the fixed time effect approach for stock market returns, which means that individual time effects are uncorrelated with other variables in the model.

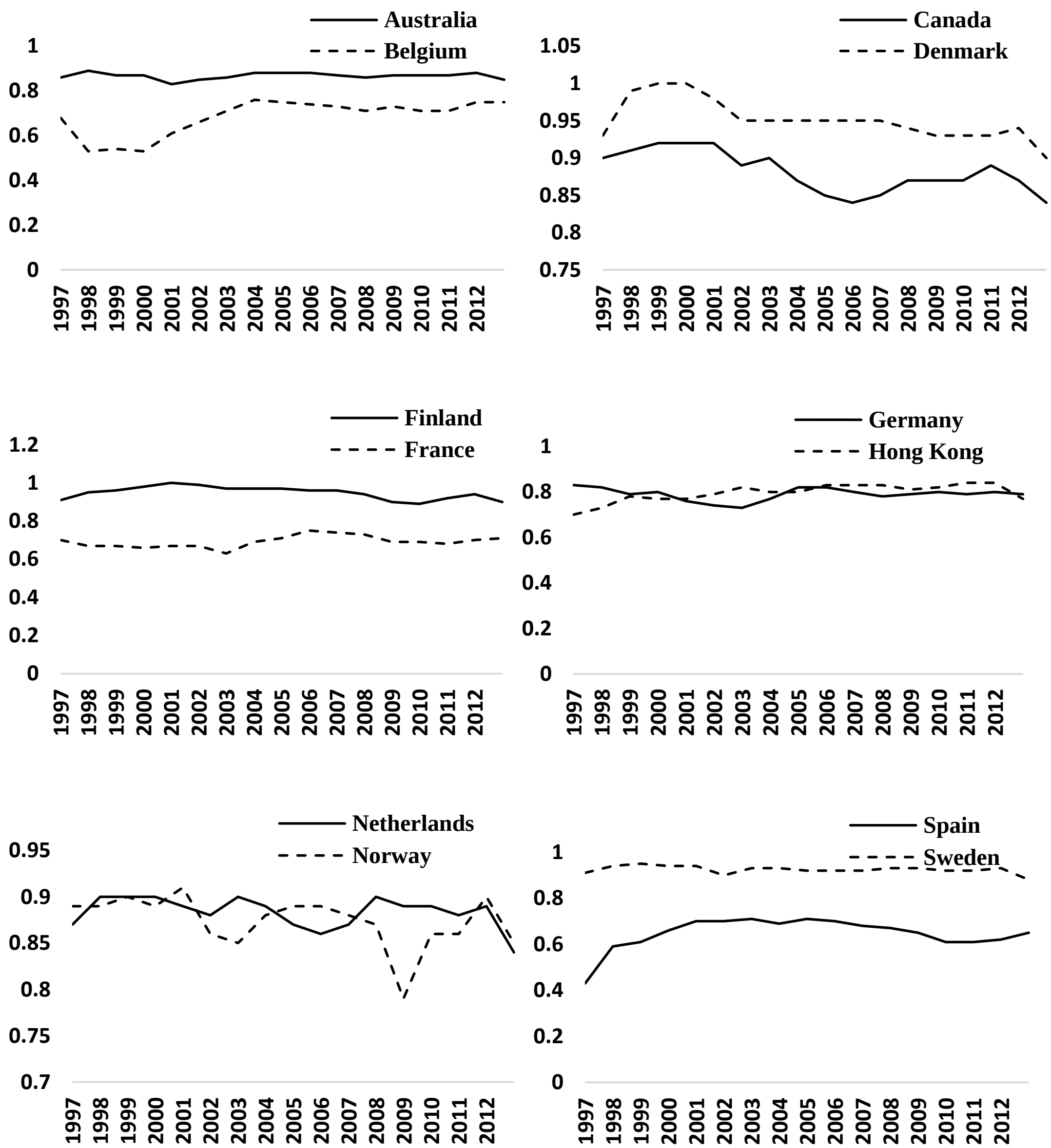
We describe data in Section 2. In Section 3, we describe models for balanced panel data and show empirical results. Then, we conclude in Section 4.

2. Data

Transparency International (TI) publishes the Corruption Perception Index (CPI) every year using survey and assessment data and ranks countries based on their CPI scores. We obtain the CPI data from 1995 to 2014 from TI (www.transparency.org). The number of countries included in the CPI increased from 41 to 175 during this time period. In addition, TI changed the range of CPI scores in 2012. In order to keep a consistent scale we calculate the ratio of each country's CPI score to the maximum CPI score. So, the maximum CPI ratio is 1 and the minimum CPI ratio is 0. While the maximum CPI ratio means the least corrupt country, the minimum CPI ratio means the most corrupt country. In other words, the higher the CPI ratio, the lower the corruption.

On the other hand, we collect annual stock market index data of countries from Fusion Media Limited (www.investing.com). Since the purpose of our study examines the effect of corruption on stock market returns and not all data are available for countries listed in the CPI, we adopt the gross domestic product (GDP) as a control variable. Ibbotson and Chen (2003) use several major factors to decompose equity returns using six methods and the GDP is one of their important factors that explain equity returns. We download annual GDP data of countries from the Federal Reserve Bank of St. Louis (www.stlouisfed.org).

After considering countries that have been consistently listed in the CPI since 1995 and their data availability, we find that 22 countries and their data are available from 1996 to 2012. These countries consist of 14 developed countries and 8 non-developed countries based on the country classification proposed by Morgan Stanley Capital International (MSCI). Annual CPI ratios of these countries are shown in Figure 1.



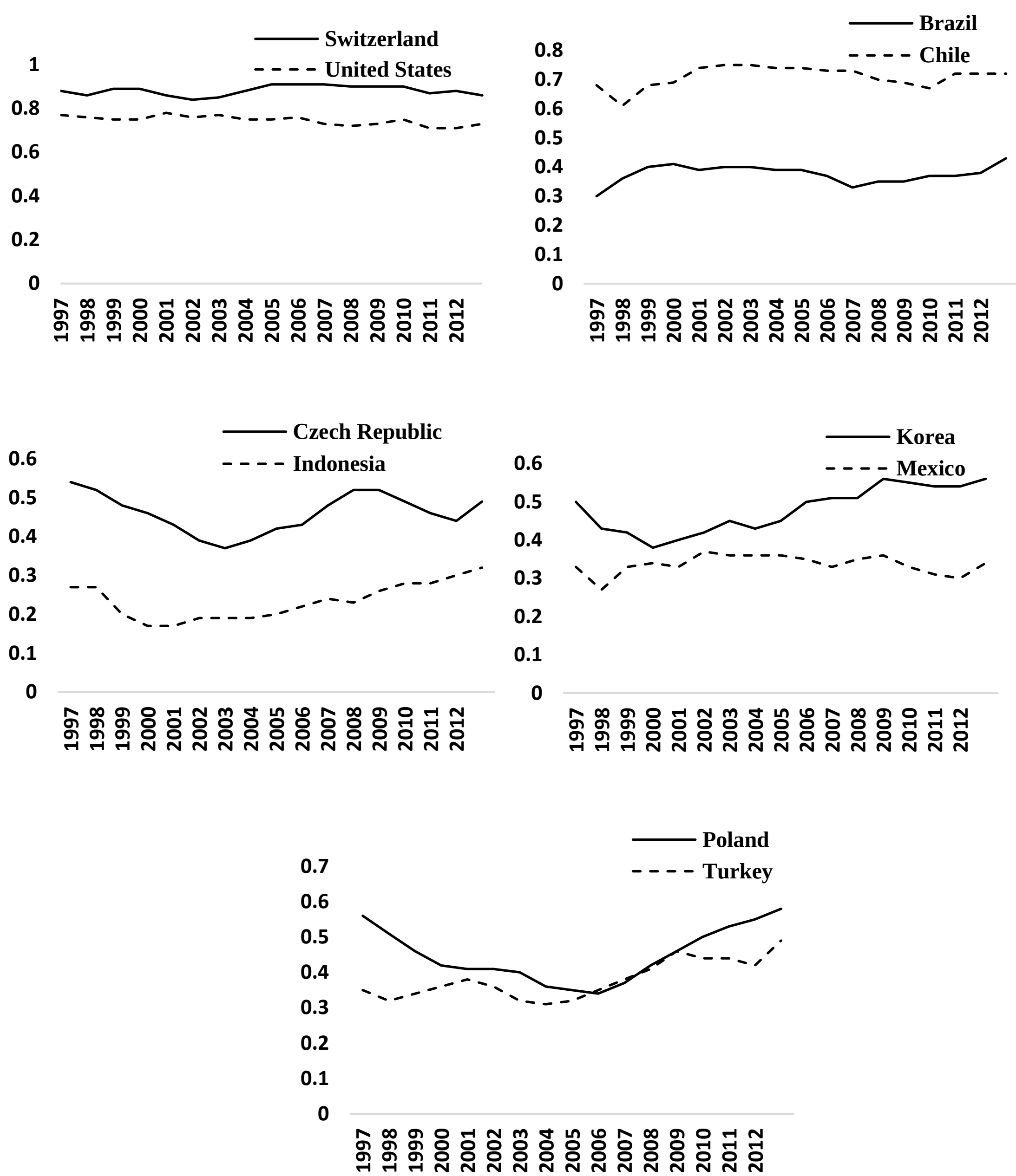


Figure I. Annual CPI ratios of 22 countries

We calculate the annual percentage change in CPI (ΔCPI), stock market index (ΔSMI), and GDP (ΔGDP). Table 1 shows the average annual change of each variable for all countries. While, for developed countries, the average of ΔCPI is 0.20% and its standard deviation is 0.89%, for non-developed countries, the average of ΔCPI is 1.08% and its standard deviation is 1.02%. The average annual stock return and standard deviation of developed countries are 7.72% and 2.86% respectively and those of non-developed countries are 19.20% and 16.08% respectively. As a result, non-developed countries have improved their corruption levels more than developed countries for this time period. In addition, non-developed countries, on average, have experienced higher stock returns than developed countries.

Table 1 Descriptive statistics

Panel A			
Developed countries	**ΔCPI**	**ΔSMI**	**ΔGDP**
Australia	-0.0005	0.0600	0.0903
Belgium	0.0093	0.0456	0.0498
Canada	-0.0041	0.0632	0.0697
Denmark	-0.0018	0.1180	0.0451
Finland	-0.0004	0.1173	0.0513
France	0.0016	0.0543	0.0451
Germany	-0.0026	0.1001	0.0363
Hong Kong	0.0066	0.0788	0.0287
Netherlands	-0.0020	0.0405	0.0502
Norway	-0.0020	0.1235	0.0805
Spain	0.0300	0.0570	0.0597
Sweden	-0.0019	0.0991	0.0555
Switzerland	-0.0012	0.0614	0.0585
United States	-0.0030	0.0623	0.0429
Average	0.0020	0.0772	0.0545
Standard deviation	0.0089	0.0286	0.0166
Panel B			
Non-developed countries	**ΔCPI**	**ΔSMI**	**ΔGDP**
Brazil	0.0253	0.1966	0.0765
Chile	0.0047	0.1189	0.0851
Czech Republic	-0.0037	0.0814	0.0856
Indonesia	0.0160	0.1982	0.1199
Korea	0.0092	0.1048	0.0654
Mexico	0.0061	0.2053	0.0659
Poland	0.0049	0.0650	0.0835
Turkey	0.0242	0.5655	0.1100
Average	0.0108	0.1920	0.0865
Standard deviation	0.0102	0.1608	0.0195

3. Empirical Models and Results

First of all, we conduct a pooled regression with a constant coefficient regardless of group and time effects to see whether the contemporary ΔCPI or lagged ΔCPI affects stock market index returns (ΔSMI). As shown in Halkos and Tzermeres (2010), we also examine if the turning point of corruption exists for stock market returns. The turning point is a value of ΔCPI at which the stock market return is maximized or minimized. The significant turning point may imply that there exists a trade-off between corruption and market efficiency so that the effect of corruption can be accelerated or decelerated as corruption is improved and its change goes beyond the turning point. To find the turning point, we use the following quadratic equation proposed by Halkos and Tzermeres (2010). The turning point is the vertex of the quadratic equation. ΔGDP is included as a control variable.

$$\Delta SMI_{it} = \alpha_0 + \varphi_1 \Delta CPI_{it} + \varphi_2 \Delta CPI_{it}^2 + \varphi_3 \Delta GDP_{it} + \varepsilon_{it} \quad (1)$$

where i is an individual group (country), and t is time (year).

Table 2 shows the pooled regression results. The second column is based on the contemporary ΔCPI regression and the third column is based on the lagged ΔCPI regression. While $\varphi_1$is not statistically significant with the contemporaryΔCPI, it is statistically significant and positive with the lagged ΔCPI. This means that an improvement in corruption from the previous time period tends to positively influence stock market returns during the current time period.

Table 2 Pooled regression results

Coefficient	Contemporary ΔCPI regression	Lagged ΔCPI regression
α_0	0.0559**	0.0412
φ_1	0.3892	0.7034*
φ_2	-4.7596	1.4983
φ_3	0.9411***	0.8961***
Adjusted R^2	0.0480	0.0548

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

On the other hand, $\varphi_2$is not statistically significant in both contemporary and lagged regressions and thus, there seems to exist no turning point of ΔCPI for stock market returns. Throughout this paper, all remaining analyses are based only on the lagged ΔCPI.

Now, we focus on the panel data analysis to investigate group and time effects. Since we use balanced panel data, we benefit from eliminating any group heterogeneity every time period. Typically, two common panel data approaches are fixed effect and random effect models. With balanced panel data, each model represents both group and time effects. All panel data analyses in our study are based on econometric techniques and steps demonstrated by Park (2009).

For the fixed group (country) effect regression, each country's dummy variable is included as a part of the intercept term and the significance of dummy variables indicate the fixed group effect regardless of time periods (years). To begin with, the following least square dummy variable (LSDV) regression can be considered.

$$R_{it} = X_{it}\beta + D_i\lambda + \varepsilon_{it} \quad (2)$$

where R_{it} is ΔSMI, X_{it} is the vector of two regressors, ΔCPI and ΔGDP, and D_i is the vector of group dummy variables. To see if there exists any fixed group effect, the null hypothesis is constructed as follows.

$Null\ Hypothesis\ (H_0): All\ dummy\ coefficients\ (\lambda) are\ equal\ to\ zero.$

Typically, the F-test is used to test the null hypothesis. The LSDV, however, does not produce consistent coefficients of dummy variables when there are so many groups (22 countries in our panel data) in panel data. Thus, we adopt the alternative approach that doesn't need dummy variables but tests the same null hypothesis. As suggested by Park (2009), the within group effect regression can be conducted to test the null hypothesis.

$$R_{it} - \bar{R}_{i\blacksquare} = (X_{it} - \bar{X}_{i\blacksquare})\beta + \varepsilon_{it} - \bar{\varepsilon}_{i\blacksquare} \quad (3)$$

where $\bar{R}_{i\blacksquare}$ is the average of dependent variables of group *i* across time periods and $\bar{X}_{i\blacksquare}$ is the average of independent variables of group *i* in a given year. Then, we test the null hypothesis using the following F-test based on the within effect regression and the pooled regression.

$$\frac{(SSE_{pooled} - SSE_{within})/(n-1)}{SSE_{within}/(nT-n-k)} \sim F(n-1, nT-n-k) \quad (4)$$

where *n* is the number of groups, *T* is the number of time periods, and *k* is the number of β coefficients. For the fixed time effect regression, we just switch group and time in Equation (3) and Equation (4).

In Table 3, we fail to reject the null hypothesis for the fixed group effect whereas we reject the null hypothesis for the fixed time effect. This means that individual fixed time effects exist across cross-sectional groups.

Table 3 Fixed effect results

	Within group effect	Within time effect
SSE	50.84	33.41
F-test statistic	0.87	13.71***

Notes: The SSE of pooled regression is 53.90. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Next, we consider the random effect regression by assuming that the random effect is a part of the error term.

$$R_{it} = X_{it}\beta + (w + \varepsilon_{it}) \quad (5)$$

where w is a random effect for either group or time with $w \sim iid(0, \sigma_w^2)$ and $\varepsilon \sim iid(0, \sigma_\varepsilon^2)$. Both random terms are independent of each other. To examine whether or not any random effect exists, the null hypothesis is as follows.

$Null\ Hypothesis\ (H_0): The\ variance\ of\ w(\sigma_w^2)\ is\ equal\ to\ zero.$

If we fail to reject the null hypothesis, it is concluded that there exists no random effect. The following Lagrange multiplier (LM) test can be used to test the null hypothesis for the random group effect.

$$\mathrm{LM} = \left[\frac{nT}{2(T-1)}\right]\left(\frac{T^2\bar{e}'\bar{e}}{e'e} - 1\right)^2 \sim \chi^2(1) \tag{6}$$

where $\bar{e}$ is the (*n x 1*) vector of group means of pooled regression residuals and $e'e$ is the SSE of the pooled regression. When we test the null hypothesis for the random time effect, we simply switch n and T and use the vector of time means of pooled regression residuals.

Table 4 Random effect results

	Random group effect	Random time effect
Mean of residuals	0.20	0.92
LM test statistic	0.29	411.17***

Notes: The SSE of pooled regression is 53.90. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

As we see in Table 4, the null hypothesis is strongly rejected for the random time effect. This means that there exists a random time effect across cross-sectional groups. Actually, the panel data analysis identifies either the fixed effect or the random effect based on how individual effects are related to variables in the model. Typically, Hausman test is used to test the following null hypothesis.

$$Null\ Hypothesis\ (H_0): Individual\ group\ or\ time\ effects\ are\ not\ correlated\ ith\ regressors\ in\ the\ model.$$

In other words, the null hypothesis states that the random effect is preferred to the fixed effect. Since, from Table 3 and Table 4, both fixed and random effect regressions confirm time effects rather than group effects, we test the null hypothesis only for the time effect. We use the following test statistic.

$$\mathrm{B}'\Sigma^{-1}\mathrm{B} \sim \chi^2(k) \tag{7}$$

where B is the vector of differences between coefficient estimates from the fixed time effect regression and the random time effect regression and $\Sigma^{-1}$is the variance of those differences. In Equation (5), however, it is not simple to estimate coefficients in the random time effect regression because random terms' variances are unknown. As a result, we employ the feasible generalized least square (FGLS) proposed by Park (2009). Basically, we transform Equation (5) by using transformed dependent and independent variables.

$$\text{Transformed } R_{it} = R_{it} - \hat{\phi}\bar{R}_{\blacksquare t} \tag{8}$$
$$\text{Transformed } X_{it} = X_{it} - \hat{\phi}\bar{X}_{\blacksquare t}$$

where $\hat{\phi}$ is a transform parameter. To estimate $\hat{\phi}$, we need SSEs obtained from the within time effect and the between time effect regressions. The SSE of the within time effect is calculated from the within time effect regression based on Equation (3). The between time effect regression is conducted as follows.

$$\bar{R}_{\blacksquare t} = \bar{X}_{\blacksquare t}\beta + \varepsilon_{it} \tag{9}$$

Then, we estimate $\hat{\phi}$ based on the following equation.

$$\hat{\phi} = 1 - \sqrt{\frac{\hat{\sigma}_\varepsilon^2}{\hat{\sigma}_\varepsilon^2 + n\hat{\sigma}_w^2}} \tag{10}$$

where $\hat{\sigma}_\varepsilon^2 = SSE_{within}/(Tn - T - k)$ and $\hat{\sigma}_w^2 = SSE_{between}/(T - K) - \hat{\sigma}_\varepsilon^2/n$.

Table 5 shows coefficient estimates in both fixed and random time effect regressions and Hausman test results. The test statistic, 3.92, is not statistically significant even at the 10% significance level. Thus, we fail to reject the null hypothesis. This means that individual time effects are uncorrelated with regressors in the model and so, the random time effect appears to be more appropriate than the fixed time effect.

Table 5 Hausman test results

Coefficient	Fixed time effect regression (Within time effect)	Random time effect regression (Transformed)
ΔCPI	0.6377**	0.6502**
ΔGDP	0.5153**	0.5631**
Hausman test statistic	3.92	

Notes: $\hat{\phi}$ is 0.7319 based on Equation (9) and (10). ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Also, from the random time effect regression in Table 5, *ΔCPI* (t = 2.02**) is positive and statistically significant. This reconfirms that an improvement in corruption is positively related to stock market returns with the existence of a random time effect across cross-sectional groups. In fact, our findings are consistent with what Mauro (1995) shows about the effect of corruption on investment and economic growth.

4. Conclusion

Corruption can be a critical issue in many countries. There are plenty of studies that have examined the effect of corruption on various sectors in our society. Unlike previous studies, our study investigates how an improvement in corruption affects stock market returns across international stock markets. While the fact that few studies have looked into the relationship between stock returns and corruption is a little surprising, we make a substantial contribution to the literature by exploring the effect of corruption on global stock markets rather than individual sectors in an economy. We implement both fixed effect and random effect models with balanced panel data that consist of cross-sectional groups and time periods. We discover that stock market returns are positively related to the improvement in corruption and have the time effect rather than the group effect. This provides evidence that as the level of corruption is improved, stock market returns tend to increase with the existence of the time effect. Empirically speaking, our study shows that corruption may play an important role in explaining stock market returns. In addition, we test whether the fixed time or the random time effect is appropriate. Our results propose that the random time effect be more appropriate than the fixed time effect. This implies that individual time effects are not correlated with other variables.

In summary, with panel data, stock market returns appear to increase with an improvement in corruption. Also, given that the time effect dominates, the random time effect turns out to be preferred to the fixed time effect. This seems to be consistent with the traditional view that explains the effect of corruption by showing that corruption hampers investments and economic growth. Our findings are important in that investors can be provided with a new insight in terms of international diversification. In other words, if the level of corruption in a country is improved, it is likely to have a positive impact on the country's stock market returns with the random time effect. In particular, our study is expected to propose alternative investment options to socially responsible or ethical investment funds in global stock markets.

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