Journal of International Business Studies (2010) 41, 1505–1524

www.jibs.net

High-level politically connected firms, corruption, and analyst forecast accuracy around the world

Charles JP Chen[1], Yuan Ding[1] and Chansog (Francis) Kim[2]

[1]China Europe International Business School, Shanghai, P. R. China; [2]City University of Hong Kong, Hong Kong, P. R. China

Correspondence:
CJP Chen, China Europe International Business School (CEIBS), 699 Hongfeng Road, Pudong, Shanghai 201206, P. R. China.
Tel: +86 21 2890 5617;
Fax: +86 21 2890 5620;
E-mail: ccharles@ceibs.edu

Received: 15 July 2008
Revised: 8 January 2010
Accepted: 12 February 2010
Online publication date: 24 June 2010

Abstract

The international business (IB) literature has widely recognized political forces as major factors that complicate the strategic decisions of multinational enterprises (MNEs). Analyses by financial intermediaries can help to reduce the risk of information asymmetry caused by such factors. Using firm-level data from 17 jurisdictions between 1997 and 2001, this study investigates the association between a firm's high-level political connections and earnings forecasts made by financial analysts, an important group of financial intermediaries. We find that, after controlling for other determinants of forecast accuracy, analysts experience greater difficulty in predicting the earnings of firms with political connections than those of firms with no such connections. However, in jurisdictions in which corruption level is relatively high, earnings forecast accuracy is influenced more by a firm's political connections. Our findings contribute to the IB literature by demonstrating that political connections exacerbate the information asymmetry between investors and managers, and also that anti-corruption measures can curb the adverse effect of political connections on the corporate information environment. These findings bear the practical implication that MNEs must consider political issues when making resource allocation decisions.

Journal of International Business Studies (2010) **41,** 1505–1524.
doi:10.1057/jibs.2010.27

Keywords: political relationships; corruption; primary data source; accounting

INTRODUCTION

Corporate political connections play an important role in many of the world's largest and most important economies (Fisman, 2001). Anecdotal evidence suggests that political connections substantially affect corporate performance not only in emerging markets, but also in developed economies. For example, in 2002 Shin Satellite (Sattel), a Thai telecom company, 53% owned by the family of the then Thai prime minister Thaksin, obtained government assistance to expand utilization of its massive capacity: The Indian government renewed its contracts with Sattel after Thaksin's whirlwind trip; Sattel made a $12 million deal with Burma right after an official visit to Thailand by a Burmese leader (Crispin, 2002). Political connections also played a role in the Enron scandal. When President Bush's advisers debated a new energy policy in the spring of 2001, Kenneth Lay (President of Enron) was the only energy executive to be invited for a one-on-one session with Vice President

Cheney, who led the effort. Mr. Lay also worked with Karl Rove and others to successfully push for their appointments to the Federal Energy Regulatory Commission (FERC), which oversaw much of Enron's business. According to Curtis Hebert Jr., ex-chairman of the FERC, President Bush replaced him with an old Enron ally from Texas soon after he refused to change his views on electricity deregulation to concur with those of Mr. Lay (Davis, 2001; Hunt, 2002).

The international business (IB) literature has shown that political connections not only affect firm-level performance and transparency, but also work hand in hand with corruption, which "produces bottle necks, heightens uncertainty, and raises costs" for cross-border business transactions (Habib & Zurawicki, 2002). Further, the IB literature has established the effects of political forces on the strategic choices of multinational enterprises (MNEs) (Smith-Hillman & Omar, 2005), and has shown that politics in general – and corporate political connections specifically – systematically influence business practices around the world (Faccio, Masulis, & McConnell, 2006; Habib & Zurawicki, 2002; Simon, 1984).

Though corporate political connections are a widespread phenomenon around the world (Faccio, 2006), and the IB literature has recognized the complex relationship between MNEs and society, research on the interactions between MNEs and politics, corruption, and corporate social responsibility is still relatively embryonic (Rodriguez, Siegel, Hillman, & Eden, 2006). We explore this relatively new research area in the IB literature by providing evidence about the effects of:

(1) high-level corporate political connections;[1]
(2) host-country corruption levels; and
(3) their interaction on the ability of financial analysts to forecast the earnings of corporations around the world.

Scholars know that "institutions matter", but do not know exactly how they matter to MNEs (Jackson & Deeg, 2008). Understanding the relationship between political connections and analyst forecasts brings us a step closer to this end, as it sheds light on the dynamic relationship between host-country politics and MNEs. Hence this is not only a less traveled path but also a relatively promising research direction.

The accuracy of earnings forecasts reflects the level of information asymmetry between (sophisticated) investors and managers (Duru & Reeb, 2002; Krishnaswami & Subramaniam, 1999), which is an important issue for both MNEs and IB scholars (Jackson & Deeg, 2008). Researchers have identified both firm-level and institutional factors that affect analyst forecasts (Brown, 1993; Clarke & Subramanian, 2006). We propose that in addition to the inherent uncertainty of earnings, political connections complicate the analyst's task, because political favoritism is usually granted covertly, and often comes in a windfall fashion that distorts the time-series pattern of reported earnings. This conjecture, which we refer to as the *analyst task difficulty hypothesis*, predicts that analyst earnings forecasts should be less accurate for firms with political connections than for firms without such connections. Alternatively, one may contend that politicians can use their influence to help connected firms smooth their earnings by transferring political favors when earnings are low, thus making their earnings more predictable. This supposition, which we refer to as the *income-smoothing hypothesis*, predicts that analyst earnings forecasts should be more accurate for firms with political connections than for firms without such connections.[2] We find that corporate political connections adversely affect financial analyst forecast accuracy, which implies that the effects from *analyst task difficulty* dominate those from *income-smoothing.*

We also propose that corruption can exacerbate the impact of political connections on analyst forecasts by aiding politicians in transferring benefits to connected firms (Faccio, 2009), obscuring the disclosures of politically connected firms about the impact of their connections on financial performance, and subjecting analysts to undue pressure from connected firms and politicians. This conjecture, which we refer to as the *corruption effect hypothesis*, predicts that the effect of political connections on analyst forecast error is more pronounced in jurisdictions with higher levels of corruption. Our empirical results support this hypothesis.

It is important to consider the two-way interaction between a host country's political system and MNE strategies, as corruption is more widespread in countries with opaque legal systems and excessive administrative discretion (Boddewyn, 1988; LaPalombara, 1994; Tanzi, 1998), and politics affects an MNE's strategic choices (Smith-Hillman & Omar, 2005). Analyzing political connections in isolation from the host country's corruption level may limit the ability of IB scholars to understand the complex nature of the relationship between corporate political connections and analyst forecasts. Our focus on the interaction between political connections and the effect of corruption explicitly considers the possibility of a two-way interaction between these two factors, as the extent of corporate political connections may alter a host country's incentives and/or ability to control corruption, and the effectiveness of a government's anti-corruption measures may in turn affect the incentives for corporations to seek political benefits. Our results suggest that political connections mask financial transparency around the world, and that the level of host-country corruption affects the discretion that politicians have in granting political favors.

The remainder of this paper proceeds as follows. The next section develops the hypotheses. The third section presents the variable measurements and empirical models. The fourth section identifies the data sources, and reports the descriptive statistics. The fifth section discusses the results of the empirical analyses. The sixth section summarizes the results of the robustness checks. The final section presents our conclusion.

HYPOTHESIS DEVELOPMENT

There are four primary tools with which the state can influence the economic performance of a firm (Stigler, 1971): direct capital subsidies, control over the entry of new rivals, the regulation of substitutes and complements, and price fixing. Each of these tools can be expected to complicate the earnings forecast task. However, political forces can also affect MNEs in a broader way. In addition to home-country political risks, MNEs may also be exposed to differential tax policies, indigenization or even nationalization, technology transfer requirements, equity ownership restrictions, and industry entry barriers.[3] Financial analysts possess expertise in forecasting the financial prospects of a firm primarily because of their understanding of the market in which the firm operates. However, analysts are less equipped to predict the outcomes of political decisions, and much less their expected effect on the future cash flow of a firm.[4]

We argue that political connections add a dimension to the task of forecasting corporate earnings. This aspect of complexity is not reflected in the historical information derived from a firm's earnings attributes, such as the time-series patterns of earnings or the characteristics of past accounting accruals, mainly because the effects of political connections are not normally recurring, nor are they cyclical. The ability of politicians to influence corporate performance is much less predictable than normal business cycles, as changes in the political landscape are not affected only by formal institutional arrangements, such as elections or appointments. Many random factors can easily and unexpectedly overwhelm the political equilibrium, including the physical health of connected politicians. For example, Fisman (2001) finds that the share prices of companies connected to Indonesia's President Suharto dropped upon news of his declining health, which indicates that, although seemingly non-financial in nature, the news of a politician's personal well-being can substantially affect the financial performance of the firms with which that politician is connected.

In addition, the impact of political connections interacts with business cycles to obscure the latter's effect on the reported accounting profits of connected firms. In times of business downturn in particular, politicians may extend assistance to prop up the reported earnings of connected firms. For example, in 2003, Silvio Berlusconi, the Italian prime minister and owner of AC Milan football club, passed the "football savior" law that "permits clubs to amortize the massive costs of player contracts over 10 years rather than the shorter lifespan of the contracts" (Kapner, 2003: 26). At a time when most clubs in Italy were faced with financial problems without increasing sales revenue, the ratification of this law interrupted the time-series patterns of earnings for AC Milan by halving its reported loss for the third quarter of 2003 to \$33.8 million, which substantially altered the financial reporting outcome and created unexpected complications for financial analysts.

Political Connections and Forecast Accuracy

Duru and Reeb (2002) argue that earnings forecast error depends on the difficulty or complexity of the forecasting task, and show that analyst earnings forecasts are less accurate for MNEs than for domestic firms. We propose five non-mutually exclusive explanations for why political connections increase information asymmetry between analysts and managers and hence make analyst forecasting more difficult.

First, political connections add a new dimension to the earnings generation process. Krueger (1974) suggests that entrepreneurs expend resources on politicians to compete for the economic rents that may be granted by the government. The payback from political connections often comes unexpectedly, which inevitably disrupts the time-series pattern of the reported earnings of connected firms, thus making the analyst forecasting task more complex.[5] These possible impacts on earnings may be either direct (favorable tax treatment, profitable projects, preferential access to markets, cheap financing, and government subsidies)[6] or indirect (injections of cash or non-cash assets that increase the future profitability of the connected firm). Either way, the increased uncertainty complicates the forecasting task of analysts. Furthermore, there is additional uncertainty about when and how much government aid the connected firm might receive. Although political forces tend to remain stable between scheduled changes in the political landscape, uncertain election outcomes and the eruption of scandals often swing the power pendulum unexpectedly, leading to erratic awarding or disruption of political favors that adversely affects the accuracy of analyst forecasts.

Second, political connections are often linked to greater opacity at the firm level (Bhattacharya, Daouk, & Welker, 2003). Government-provided shielding from market monitoring mechanisms (e.g., regulatory disclosure requirements and investor demands for transparency) may allow managers of politically connected firms to enjoy more discretion over financial disclosure. This increases the information asymmetry between analysts and managers, which in turn makes the analyst forecasting task more difficult.

Third, variation in investor demand for information can affect the properties of analyst forecasts (Barth, Kasznik, & McNichols, 2001). Politically connected firms have less need to raise capital from the public, because they can obtain privileged loans from banks that are influenced by politicians (Claessens, Feijen, & Laeven, 2008; Faccio et al., 2006). A firm's need to access equity financing affects the level of investor demand for its earnings forecast information, which in turn affects the expected benefit of providing accurate earnings forecasts. Analysts may thus have less incentive to develop expertise in forecasting the earnings of connected firms, which may adversely affect their forecast accuracy.

Fourth, Chaney, Faccio, and Parsley (2007) show that the quality of accounting information is significantly worse for politically connected firms than for their non-connected counterparts, and that firms with stronger political connections have the worst-quality accounting information. Their evidence supports the notion that politically connected firms attempt to obscure their gains from politicians in their reported accounting information. Previous studies have found that accounting information quality is positively correlated with analyst forecast accuracy (Hope, 2003). Hence we can expect the earnings forecasts of connected firms to be less accurate than those of non-connected firms.

Finally, our proposal that political decisions increase the error in the earnings forecasts of connected firms is consistent with previous studies recording that the equity value of politically connected firms can be easily affected by political events (Faccio, 2006; Fisman, 2001; Roberts, 1990). Fisman (2001) argues that "in Southeast Asia, political connectedness, rather than fundamentals such as productivity, [is] the primary determinant of profitability and this had led to distorted investment decisions." In addition, when government officials lose their political influence, cash flow into the firms with which they were connected will dwindle, and so too will firm value, as is indicated by the findings of Fisman (2001) and Faccio and Parsley (2006). Using a series of US cases, Hillman, Zardkoohi, and Bierman (1999) also show that political links positively affect firm value. The unpredictable nature of the adverse effect of falling out of political favor further complicates the earnings forecasting task.

These non-mutually exclusive explanations for why corporate political connections make the task of earnings forecasting more difficult collectively predict that analysts are less likely to forecast the future earnings of politically connected firms accurately.[7]

Hypothesis 1: Firms with political connections are associated with less accurate analyst earnings forecasts, *ceteris paribus*.

Political Connections, Corruption, and Analyst Earnings Forecast Accuracy

Corruption as a social and economic phenomenon has attracted much academic attention, including that from IB scholars. It can exist either explicitly in the form of bribery or implicitly as "commission" or exchange of favors. Though some early studies consider it a necessary facilitator for executing business transactions in societies where corruption is ubiquitous, more recent findings in the management and IB literature generally support the view that condemns corruption as a social evil, as it increases transaction costs and creates social-cultural barriers to foreign direct investment (FDI) (Cuervo-Cazurra, 2006; Zhao, Kim, & Du, 2003).

Faccio (2009) argues that politicians do not have equal influence in all countries. She finds that leverage is significantly higher for connected firms in Malaysia, Russia, and Thailand; that connected firms are subject to lower tax rates in most countries, but especially low rates only in Russia, where connected firms enjoy an extraordinary 73.27% lower tax rate; and that connected firms exhibit a lower return on equity in all countries, but that this difference is significant only in Russia and Thailand. Interestingly, the countries in which connected firms enjoy the most significant political benefits are often those that are regarded as having less effective legal systems and higher levels of corruption (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1998). In a theoretical paper, Boddewyn (1988: 357) argues that "countries with poorly differentiated economic, political and social structures, without fairly independent institutions and/or condoning the political enrichment of leaders are more amenable to corruption by MNEs."

Corruption creates injustice in the legal system and depreciates the value of public scrutiny. In countries with high levels of corruption, financial media may be reduced to mimicking the voices of powerful politicians or corporations connected to them. Financial analysts who publish forecasts that are not preferred by connected firms or their political attaché may be subject to undue pressure or harassment. As a result, analysts may be encouraged or even forced to forecast earnings to please the connected firms and their politicians, even though such forecasts may not be consistent with their professional judgment. Moreover, the results of DiRienzo, Das, Cort, and Burbridge (2007) suggest that in countries with high levels of corruption, the lack of transparency increases information asymmetry and results in fewer transgressions by individuals, businesses, and the government. Hence we propose that the benefits and costs of acquiring political favor may vary across jurisdictions. Specifically, as the level of corruption indicates how easy it is to reap the benefits of political connections, it can be expected that the financial results of connected firms will be more influenced by the payoffs they receive from politicians in jurisdictions where a high level of corruption creates more opportunities for distributing political favors. Our second hypothesis is stated as follows:

Hypothesis 2: The effect of political connections on analyst forecast error is stronger in jurisdictions with higher levels of corruption, *ceteris paribus*.

MEASUREMENT OF VARIABLES AND EMPIRICAL MODELS

Measuring Political Connections and Corruption Level

This study focuses on high-level corporate political connections by following Faccio's (2006: 369) definition whereby

> a company is identified as being connected with a politician if at least one of its large shareholders (anyone controlling at least 10% of voting shares) or one of its top officers (CEO, president, vice-president, chairman, or secretary) is a member of parliament, a minister, or is closely related to a top politician or party.[8]

This variable takes the value of 1 for connected firms and 0 otherwise.

As discussed, the impact of political connections on the analyst forecasting task is influenced by the expected net benefit of political favoritism, which in turn is jointly determined by the level of corruption in the country. To measure the level of corruption, we employ the Corruption Perceptions Index (CPI) provided by Transparency International. It reflects the annual ranking of 180 countries around the world, produced by expert assessments and opinion surveys from multiple sources (e.g., 11 independent institutions in 2008). The CPI captures the overall extent of corruption (frequency and/or size of bribes) in the public and political sectors. The valuation of corruption in countries is conducted by country experts, both non-resident and resident. In determining the mean value for a country, the ranks reported by each individual source are aggregated and standardized. Countries with relatively low levels of perceived corruption achieve high CPI scores, which could also be viewed as the effectiveness of country-level anti-corruption efforts.[9] We construct a corruption measure (Corrupt) which is CPI scaled by its maximum value and multiplied by a negative one to facilitate discussion of the empirical results. Therefore high Corrupt values indicate high levels of corruption hereafter.

Measuring Forecast Error

In the literature on financial analyst forecasting, the absolute value of forecast error has been employed as a proxy for analyst ability to accurately forecast earnings, signed forecast error has been used as a proxy for forecast optimism, and the dispersion of forecasted earnings has been employed as a proxy for the disagreement among analysts. To make this study more focused, we concentrate on forecast error in testing our hypotheses.[10] Following previous studies (Duru & Reeb, 2002; Hope, 2003), we define forecast error as the absolute value of the difference between forecasted and actual earnings, scaled by the stock price at time $t-1$ (the beginning of year t).[11]

$$\text{Fcst\_Error}_t = \frac{\left|\text{FORECAST}_t^{t-1} - \text{EARN}_t\right|}{\text{PRICE}_{t-1}} \quad (1)$$

where Fcst_Error_t is the analyst consensus forecast error in period t, FORECAST_t^{t-1} is the 3-month average consensus forecast of earnings per share for period t compiled by IBES during the 3-month period from 8 months to 6 months before the fiscal year-end, EARN_t is the actual earnings per share before extraordinary items for period t, and PRICE_{t-1} is the stock price at the end of the fiscal year ($t-1$).[12]

Control Variables

To make an incremental contribution to the literature by testing our hypotheses, it is necessary to control for factors that have already been identified by prior studies as systematically affecting analyst forecast accuracy. Table 1 summarizes the definitions of and data sources for the test and control variables. Our choice of control variables is guided by Francis, LaFond, Olsson, and Schipper (2004), Hope (2003), and Duru and Reeb (2002). We include the number of analysts following a firm (Num_Fcst) as a proxy for analyst incentive to reduce forecast error in the ongoing competition for reputation. Disclose represents the Center for International Financial Analysis and Research (CIFAR) firm-level disclosure index (Hope, 2003), which proxies for the firm-level transparency of financial information disclosures. Leverage is computed as the ratio of long-term debt to shareholder equity. Acc_Quality is the standard deviation of a firm's residuals from the annual cross-sectional estimations of the modified Dechow–Dichev model over the preceding 5 years (Chaney et al., 2007). Thus higher Acc_Quality values indicate lower levels of firm's accrual quality.

Following Francis et al. (2004), we control for the innate sources of earnings attributes, including firm size[13] (Size), variation in cash flow from operations

Table 1 Main variables used in this study

Variable	*Definition*	*Data source(s)*
Fcst_Error	Absolute value of the difference between the mean forecast and actual EPS scaled by the stock price at the beginning of the fiscal year.	I/B/E/S
Polit_Conn	An indicator variable for politically connected firms.	Faccio (2006)
Corrupt	Corruption index. The CPI value provided by Transparency International is higher for countries with lower levels of perceived corruption. We scale it by the maximum value of this variable, and multiply it by a negative 1 in all regression analysis to facilitate discussion of the empirical results.	Transparency International
Num_Fcst	Number of analyst forecasts.	I/B/E/S
Disclose	Firm-level total annual report disclosure scores.	Hope (2003), CIFAR
Leverage	Ratio of long-term debt to shareholder equity.	Global Vantage
Acc_Quality	Standard deviation of a firm's residuals from year $t-4$ to t taken from time-series cross-sectional estimations of fitted values that regress total current accruals on change in sales, GPPE, and industry and time dummies. Refer to Chaney *et al.* (2007) for details.	Global Vantage
Size	Log of total assets.	Global Vantage
σ(CFO)	Standard deviation of a firm's rolling 10-year cash flow from operations, deflated by the average of the beginning and end balances of total assets.	Global Vantage
σ(Sales)	Standard deviation of a firm's rolling 10-year sales revenue, deflated by the average of the beginning and end balances of total assets.	Global Vantage
Neg_Earn	Proportion of losses over the preceding 10 years.	Global Vantage
OperCycle	Log of the sum of a firm's days of accounts receivable and days of inventory.	Global Vantage

(σ(CFO)), variation in sales revenue (σ(Sales)), loss frequency (Neg_Earn), and length of operating cycle (OperCycle). We also control for the industry in which the firm operates using the Fama–French 48-industry classification (Fama & French, 1997).[14] To ensure brevity, readers are directed to the cited references for a detailed discussion of these control variables.

This gives us a model with which to test our *analyst task difficulty* hypothesis (Hypothesis 1).

$$\begin{aligned}\text{Fcst\_Error}_{it} = {} & \alpha_0 + \alpha_1\text{Polit\_Conn}_{it} + \alpha_2\text{Num\_Fcst}_{it} \\ & + \alpha_3\text{Disclose}_{it} + \alpha_4\text{Leverage}_{it} \\ & + \alpha_5\text{Acc\_Quality}_{it} + \alpha_6\text{Size}_{it} \\ & + \alpha_7\sigma(\text{CFO})_{it} + \alpha_8\sigma(\text{Sales})_{it} \\ & + \alpha_9\text{Neg\_Earn}_{it} + \alpha_{10}\text{OperCycle}_{it} \\ & + \Sigma\alpha_t\text{YearDummy}_t \\ & + \Sigma\alpha_j\text{IndustryDummy}_j + \varepsilon_{it}\end{aligned} \tag{2}$$

The following model is used to test our *corruption effect* hypotheses (Hypothesis 2).

$$\begin{aligned}\text{Fcst\_Error}_{it} = {} & \beta_0 + \beta_1\text{Polit\_Conn}_{it} + \beta_2\text{Corrupt}_{it} \\ & + \beta_3\text{Polit}_{it}\times\text{Corrupt\_C}_{it} \\ & + \beta_4\text{Num\_Fcst}_{it} + \beta_5\text{Disclose}_{it} \\ & + \beta_6\text{Leverage}_{it} + \beta_7\text{Acc\_Quality}_{it} \\ & + \beta_8\text{Size}_{it} + \beta_9\sigma(\text{CFO})_{it} + \beta_{10}\sigma(\text{Sales})_{it} \\ & + \beta_{11}\text{Neg\_Earn}_{it} + \beta_{12}\text{OperCycle}_{it} \\ & + \sum\beta_t\text{YearDummy}_t \\ & + \sum\beta_j\text{IndustryDummy}_j + v_{it}\end{aligned} \tag{3}$$

where the variable on the left-hand side is analyst forecast error (Fcst_Error), and Polit_Conn is an indicator variable that takes the value 1 for politically connected firms and 0 otherwise. Corrupt is the CPI index scaled by its maximum value and multiplied by a negative one. The variable Polit $\times$ Corrupt_C is the interaction term between Polit_Conn and Corrupt_C, which is Corrupt minus its mean value. This centering process is a common econometric technique for avoiding collinearity between Corrupt and its interaction with Polit_Conn. Smith and Sasaki (1979) suggest that this process will yield low correlations between the product term and the component variables of the term. This transformation will leave unchanged the values of coefficients of Corrupt and the multiplicative term of political connection and Corrupt, but will alter the values of the coefficient of political connection (Polit_Conn) and the intercept (Jaccard, Wan, & Turrisi, 1990).

DATA SOURCES AND SAMPLE DESCRIPTION

Sample Selection

We have constructed a one-to-all, by-year, by-country, and by-industry matched sample for our empirical tests.[15] The sample excludes industries in which there were no politically connected observations in the country, year, or industry. This sampling approach minimizes the probability that our findings are caused by year, country, or industry differences between connected and non-connected firms. The Global Vantage and International I/B/E/S databases are used to construct the sample. We start with a list of politically connected firms, generously provided by Mara Faccio, which includes 541 companies in 35 jurisdictions. We identify 344 of these companies using Global Vantage information from the period 1997–2001. Companies without a Global Vantage identifier (GVKEY) are not included in the sample. We further exclude 14 utility companies and financial institutions, and also companies without sufficient information to compute the analyst forecast attributes (121 firms), firm-level disclosure scores (60 firms), innate accounting quality measures (8 firms), or matched firms (27 firms). Our final sample consists of 114 politically connected firms with 349 firm–year observations in 17 jurisdictions between 1997 and 2001.

Table 2 shows 5368 firm–year observations for 1895 non-connected firms in the same period, which indicates that there are far more non-connected firms than connected firms. As discussed in the section on the robustness checks, a bootstrapping procedure and one-to-one, one-to-three, and one-to-five matched samples are employed to address the concern that the number of politically connected observations may not be sufficient. It is possible that some connected firms have been misclassified as non-connected, because our definition focuses on high-level corporate political connections. However, neither the small sample size nor misclassification errors of this type would create a bias toward finding significant results; therefore we do not consider them to be a significant threat to the internal validity of our study, unless our results are not statistically significant in the expected direction. Panel A of Table 2[16] also shows that the UK sample represents almost

Table 2 Sample distribution

Jurisdiction	*Connected firms*		*Non-connected firms*		*CPI*
	No. of firms	*Firm–years*	*No. of firms*	*Firm–years*	
Panel A: Jurisdictions, connected and non-connected firms, and Corruption Perceptions Index (CPI)					
Australia	1	2	4	7	8.62
Canada	1	1	4	4	9.12
France	7	19	36	82	6.68
Germany	2	7	13	23	7.82
Hong Kong	1	1	1	1	7.68
Indonesia	4	8	7	19	2.00
Italy	2	4	4	7	4.88
Japan	17	58	768	2089	6.38
Korea	1	1	2	2	4.10
Malaysia	23	78	50	124	5.04
Singapore	3	7	8	16	9.04
Spain	1	4	3	11	6.52
Sweden	1	3	4	6	9.34
Switzerland	3	5	19	28	8.68
Taiwan	4	7	11	18	5.46
UK	35	112	282	800	8.50
USA	8	32	679	2131	7.60
Total	114	349	1895	5368	

Industry	*Connected firms*		*Non-connected firms*	
	No. of firms	*Firm–years*	*No. of firms*	*Firm–years*
Panel B: Industry breakdown[a]				
Agriculture	2	4	3	5
Food products	4	11	7	24
Recreational products	1	4	13	39
Entertainment	2	4	2	3
Printing and publishing	4	15	11	29
Consumer goods	2	5	48	135
Pharmaceutical products	3	9	134	448
Chemicals	5	15	99	337
Rubber and plastic products	1	1	1	1
Textiles	2	2	3	3
Construction materials	13	42	49	130
Construction	5	18	38	132
Steel works, etc.	4	16	63	207
Machinery	5	11	127	307
Automobiles and trucks	4	9	54	64
Defense	1	5	4	13
Petroleum and natural gas	3	8	81	273
Telecommunications	4	9	13	27
Personal services	1	5	5	15
Business services	8	19	401	1055
Computers	4	5	40	42
Electronic equipment	4	21	238	772
Transportation	11	31	131	425
Wholesale	9	30	186	458
Retail	7	29	137	402
Restaurants, hotels, motels	5	21	7	22
Total	114	349	1895	5368

[a]Utilities (4900–4949) and Finance (6000–6999) industries are not included in our sample.
This table reports the distributions of politically connected and non-connected firms across countries (Panel A) and industries (Panel B). The Corruption Perceptions Index (CPI) was provided by Transparency International (http://www.transparency.org/). The higher CPI value is assigned to a country with a lower level of perceived corruption.

one-third of all of the politically connected firms in our study, and that less than 0.1% of the firms in the US sample have political connections, a figure that is substantially lower than the sample average of more than 4%. We address the issue of a possible sampling bias effect by testing our hypotheses on a sample without UK or US firms in the robustness checks.

Panel B of Table 2 indicates that our sample is well distributed across industries. A large number of them are in the traditional industries such as construction materials, construction, steelworks, machinery, electronic equipment, transportation, wholesale, and retail. However, the industry that has the largest number of observations among the non-traditional industries is business services, which can be explained by two factors. First, the recent growth in the service industry has added many new members to it. Second, Global Vantage, the database used for this study, tends to cover mature companies in the developed economies while under-representing developing economies. In contrast to common belief, high-level political connections do not cluster in the pharmaceuticals, petroleum and defense industries in our sample. A possible explanation may be that these are very sensitive industries that attract increased media attention and public scrutiny: consequently corporate political connections may be concealed, making them more difficult to track though public information.[17]

Descriptive Statistics

Table 3 presents the descriptive statistics for the sample after winsorizing extreme values at the first percentile. The sample contains 349 (114) politically connected firm–year observations (firms) and 5368 (1895) non-connected firm–year observations (firms). Consistent with the *analyst task difficulty hypothesis*, which predicts that political connections complicate the task of forecasting earnings, the mean value of forecast error is significantly greater for politically connected firms than for non-connected firms. On average, countries with higher Corrupt scores (higher levels of perceived corruption) have a higher proportion of firms with political connections, as the mean value of Corrupt is significantly higher for the connected group. Politically connected firms have significantly higher numbers of analysts following them than non-connected firms. Firms with political connections have lower firm-level disclosure scores than their non-connected peers, and the annual reports of connected firms tend to be less transparent. Given that the mean and median values of firm size (Size) are higher for politically connected firms, the difference in the number of analysts following a firm is probably due to connected firms being generally larger and more conspicuous than non-connected firms. Consistent with Chaney et al. (2007), accounting information quality (σ(CFO) and Acc_Quality) is significantly better for non-connected firms than for connected firms. Politically connected

Table 3 Descriptive statistics

	Political			*Non-political*			*t-stat.*	*z-stat.*
	Mean	*Median*	*Std*	*Mean*	*Median*	*Std*		
Fcst_Error	0.0636	0.0154	0.11	0.0365	0.0112	0.08	4.35***	3.92***
Corrupt	−0.6916	−0.7100	0.16	−0.7180	−0.7500	0.10	3.00***	1.25
Num_Fcst	9.3160	6.4444	8.30	6.5918	4.0000	6.63	6.01***	6.05***
Disclose	0.8240	0.8332	0.12	0.8629	0.8333	0.12	−5.75***	−3.93***
Leverage	0.6766	0.4175	1.04	0.5857	0.2486	1.20	1.57	4.69***
Acc_Quality	0.0779	0.0601	0.05	0.0724	0.0581	0.05	1.84*	1.82*
Size	6.5215	6.7321	2.10	5.9215	5.9865	1.71	5.23***	6.53***
σ(CFO)	0.1202	0.0952	0.09	0.1118	0.0849	0.10	1.72*	3.86***
σ(Sales)	0.2115	0.1521	0.19	0.2245	0.1581	0.20	−1.25	−1.09
Neg_Earn	0.1338	0.0000	0.21	0.2100	0.1000	0.28	−6.39***	−5.18***
OperCycle	2.8968	4.1772	2.50	3.6633	4.6780	2.21	−5.58***	−5.31***
No. of observations		349			5368			
(No. of firms)		(114)			(1895)			

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed).
This table reports the mean, median, and standard deviation values of the variables used in the regression analyses from 1997 to 2001.
See Table 1 for the definitions of variables used in this table.

firms report losses less frequently, as the mean and median values of the proportion of years with reported negative earnings (Neg_Earn) are significantly smaller for the connected group. Firms with political connections also have a shorter average operating cycle. These results are generally consistent with our argument that connected firms enjoy political benefits that complicate the earnings generation process and are inconsistent with the income-smoothing argument. We next discuss the results of the correlation analysis.

EMPIRICAL ANALYSIS

Correlation Analysis Results

Table 4 presents the results of the correlation analysis, with the Spearman correlations reported in the lower diagonal and the Pearson correlations reported in the upper diagonal. As our measure of interest (Polit_Conn) is a dichotomous variable, we focus on its Spearman correlations with forecast error. Although political connections are significantly positively correlated with forecast error, as predicted, we do not attempt to draw any conclusions from this, because these results are obtained without controlling for the effect of several factors that have been identified in previous studies as affecting analyst forecast error. After all, our hypotheses emphasize the incremental effect of political connections. The results of the correlation analysis for the control variables are generally consistent with our expectations, in that they indicate that connected firms are more prevalent in jurisdictions with higher levels of perceived corruption, and are followed by more analysts, are larger, and are less transparent (Disclosure) than non-connected firms. In addition, connected firms report losses less frequently and exhibit shorter operating cycles and higher leverage, although they have a lower accrual quality. The correlations among the variables on the right-hand side are generally low and do not indicate strong evidence of multicollinearity.[18] As the results of our univariate analyses are inconsistent with the *income-smoothing hypothesis* proposed at the beginning of the paper, subsequent multivariate analyses focus on testing the *analyst task difficulty hypothesis*.

Regression Results

The results presented in Table 5 are obtained by using the Newey–West regression, which reports heteroskedasticity- and autocorrelation-consistent covariance matrix estimators for testing the incremental effect of political connections (Polit_Conn) on forecast error. Table 6 reports the results for testing the effect of corruption (Corrupt) on analyst forecast error. To control for the clustering effect of corruption (Corrupt) at the jurisdiction level, we employ panel-corrected standard errors, as suggested by Petersen (2008), to obtain the results reported in Table 6. Our findings should thus be robust to both serial and within-country cross-sectional correlation.[19]

Four models are reported in Tables 5 and 6. Model 1 includes only the experimental variables (Polit_Conn in Table 5; Polit_Conn, Corrupt, and Polit_Corrupt_C in Table 6); Model 2 adds three control variables (the number of analyst forecasts, disclosure level, and firm leverage), as in Hope (2003); Model 3 includes one more control variable (accrual quality) to control for its effect on forecast accuracy; and the five innate factors identified by Dechow and Dichev (2002) are added to Model 4 to bring control for the effect of the difference in weightings assigned by analysts to various types of earnings quality (i.e., innate vs discretionary) in formulating their earnings forecasts.

Table 5 shows that the coefficients of political connections (Polit_Conn) range from 0.0211 to 0.0291 in Models 1–4 and are statistically significant at less than the 1% level, indicating that analysts issue less accurate forecasts for firms with political connections. To gauge the economic significance of the coefficients of Polit_Conn, we use the average price of our sample ($27.78, not reported) to convert the coefficients into dollar amounts. The estimated coefficients of Polit_Conn range from $0.59 to $0.81 in analyst forecast error, which ranges from 67.8% to 93.1% of the average forecast of $0.87 in our sample. Political connections thus generate non-trivial differential amounts of analyst forecast error. As in previous studies, analyst coverage (Num_Fcst) and the CIFAR firm-level disclosure scores (Disclose) are significantly negative, which is consistent with the notion that analyst coverage and firm disclosure reduce analyst forecast error. In contrast, leverage increases forecast error. The coefficient of accrual quality (Acc_Quality) in Model 3 is significantly positive, indicating that analyst forecast error increases for firms with lower-quality accruals. However, once the five innate factors identified by Dechow and Dichev (2002) (Size, σ(CFO), σ(Sales), Neg_Earn, and OperCycle) are included in Model 4, the significance of accrual quality vanishes, meaning that analysts assign different weightings to different sources of earnings quality (i.e., innate vs discretionary) in

Table 4 Correlation analysis results

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1	Fcst_Error	1.0000	0.0807	0.1934	−0.2054	−0.1733	0.1236	0.0347	−0.1238	0.0222	0.0485	0.1469	0.0314
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0087)	(<0.0001)	(0.0927)	(0.0002)	(<0.0001)	(0.0176)
2	Polit_Conn	0.0519	1.0000	0.0619	0.0962	−0.0760	0.0183	0.0262	0.0824	0.0209	−0.0157	−0.0670	−0.0820
		(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)	(0.1672)	(0.0480)	(<0.0001)	(0.1135)	(0.2346)	(<0.0001)	(<0.0001)
3	Corrupt	0.2189	0.0165	1.0000	−0.0827	−0.4351	0.1690	−0.1187	−0.1196	−0.2579	−0.1057	−0.0729	0.1678
		(<0.0001)	(0.2116)		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
4	Num_Fcst	−0.4217	0.0801	−0.1543	1.0000	0.2626	−0.0471	−0.0125	0.4095	0.0395	0.0153	−0.1481	−0.0840
		(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)	(0.0004)	(0.3439)	(<0.0001)	(0.0028)	(0.2475)	(<0.0001)	(<0.0001)
5	Disclose	−0.2981	−0.0520	−0.5509	0.2982	1.0000	−0.1828	0.0940	0.1230	0.2897	0.0580	0.2664	−0.2600
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
6	Leverage	0.1615	0.0620	0.1863	0.0165	−0.2723	1.0000	−0.0478	−0.0246	−0.0984	0.0695	0.0843	0.0572
		(<0.0001)	(<0.0001)	(<0.0001)	(0.2119)	(<0.0001)		(0.0003)	(0.0625)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
7	Acc_Quality	0.0076	0.0241	−0.1280	0.0157	0.1327	−0.1278	1.0000	−0.1874	0.5016	0.3046	0.0754	−0.0856
		(0.5649)	(0.0683)	(<0.0001)	(0.2358)	(<0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
8	Size	−0.1757	0.0864	−0.0320	0.4082	0.0377	0.2231	−0.1872	1.0000	−0.1521	−0.1799	−0.2177	0.0163
		(<0.0001)	(<0.0001)	(0.0156)	(<0.0001)	(0.0043)	(<0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)	(0.2175)
9	σ(CFO)	−0.0570	0.0510	−0.4146	0.1329	0.4240	−0.1696	0.5126	−0.1091	1.0000	0.2554	0.4102	−0.2599
		(<0.0001)	(0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)
10	σ(Sales)	−0.0075	−0.0144	−0.1804	0.0648	0.1376	−0.0164	0.3311	−0.1906	0.3229	1.0000	−0.0040	−0.0889
		(0.5721)	(0.2768)	(<0.0001)	(<0.0001)	(<0.0001)	(0.2165)	(<0.0001)	(<0.0001)	(<0.0001)		(0.7608)	(<0.0001)
11	Neg_Earn	0.2042	−0.0685	−0.0536	−0.1454	0.2145	0.0490	0.0688	−0.1888	0.2797	0.0408	1.0000	−0.1789
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0002)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0021)		(<0.0001)
12	OperCycle	0.0854	−0.0702	0.2207	−0.1011	−0.2603	0.0678	−0.0530	0.0317	−0.2049	−0.1708	−0.0307	1.0000
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0167)	(<0.0001)	(<0.0001)	(0.0202)	

This table reports the Pearson (above the diagonal) and Spearman (below the diagonal) correlations among the variables used in this paper for 5717 firm–year observations for the period 1997–2001. The significance levels are in parentheses. See Table 1 for the definitions of variables used in this table.

Table 5 Newey–West standard error regression results on the effect of political connections (absolute *t*-values in parentheses)

Independent variable	*Pred. sign*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*VIF*
Intercept		0.0405***	0.1036***	0.0980***	0.1029***	
		(3.67)	(6.12)	(5.78)	(5.76)	
Polit_Conn	+	0.0211***	0.0285***	0.0281***	0.0291***	1.07
		(2.92)	(4.08)	(4.04)	(4.19)	
Num_Fcst	−		−0.0022***	−0.0022***	−0.0015***	1.44
			(15.16)	(14.91)	(9.22)	
Disclose	−		−0.0623***	−0.0669***	−0.0803***	1.99
			(3.89)	(4.18)	(5.10)	
Leverage	+		0.0062***	0.0063***	0.0036***	1.14
			(4.16)	(4.24)	(2.47)	
Acc_Quality	+			0.0856***	0.0306	1.41
				(3.51)	(1.01)	
Size	+				−0.0004	1.37
					(0.51)	
σ(CFO)	+				0.0003	1.75
					(0.02)	
σ(Sales)	+				0.0137**	1.28
					(1.87)	
Neg_Earn	+				0.0638***	1.72
					(10.23)	
OperCycle	+				0.0009*	1.26
					(1.63)	
Year dummies		Yes	Yes	Yes	Yes	
Industry dummies		Yes	Yes	Yes	Yes	
R^2		0.0338	0.0837	0.0862	0.1184	
F-statistics		14.25***	103.391***	15.607***	41.608***	
Adjusted R^2		0.0314	0.0809	0.0833	0.1148	
No. of firms		2009	2009	2009	2009	
(Connected)		(114)	(114)	(114)	(114)	
No. of observations		5717	5717	5717	5717	
(Connected)		(349)	(349)	(349)	(349)	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (one-tailed).
The dependent variable, Fcst_Error, is the absolute value of the difference between the mean forecast and actual EPS scaled by the stock price at the beginning of the fiscal year. See Table 1 for the definitions of explanatory variables used in this table. Year and industry dummies are included in the regression, but are not tabulated. The coefficient estimates are reported. The *t*-values are based on clustered standard errors (Petersen, 2008). The *F*-statistic in Model 1 tests the overall significance of the regression in Model 1. The *F*-statistic in Model 2 examines the incremental contribution of the explanatory variables newly added to Model 1 in Model 2. The *F*-statistic in Model 3 tests the incremental contribution of the explanatory variable(s) newly added to Model 2 in Model 3. The *F*-statistic in Model 4 tests the incremental contribution of the explanatory variable(s) newly added to Model 3 in Model 4.

issuing earnings forecasts. These results support Hypothesis 1 that corporate political connections complicate the task of forecasting earnings.

The results in Table 6 show that political connections (Polit_Conn) continue to be significantly positive after the corruption level variable (Corrupt) is included, which as expected has a significantly positive sign in all four models. What is more interesting is that the interaction term between these two variables (Polit_Corrupt_C) is significantly positive in all four models at less than the 1% level, which suggests that corruption exacerbates the undesirable effect of corporate political connections on forecast accuracy.

Once the multiplicative term (Polit_Corrupt) is added to a multivariable regression model, the coefficient of each constituent variable no longer describes its average effect on the independent variable, regardless of the level of the other constitutive variable. With the interaction term (Polit_Corrupt_C), the coefficient of political connection (Polit_Conn) describes its *conditional* effect on

Table 6 Results of the Newey–West standard error regression on the influence of political connections and corruption index for cluster effects (absolute *t*-values in parentheses)

Independent variable	*Pred. sign*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*VIF*
Intercept		0.1325***	0.1487***	0.1450***	0.1415***	
		(4.90)	(3.73)	(3.90)	(4.05)	
Polit_Conn	+	0.0152**	0.0228***	0.0223***	0.0230***	1.09
		(1.77)	(2.96)	(2.94)	(3.13)	
Corrupt	+	0.1249***	0.0988**	0.1057**	0.0998**	1.75
		(4.00)	(1.99)	(2.27)	(1.81)	
Polit_Corrupt_C	+	0.1325***	0.1570***	0.1504***	0.1541***	1.29
		(2.88)	(3.31)	(3.30)	(3.23)	
Num_Fcst	−		−0.0023***	−0.0022***	−0.0017***	1.45
			(4.56)	(4.22)	(5.51)	
Disclose	−		−0.0266	−0.0300	−0.0488*	2.22
			(0.56)	(0.69)	(1.34)	
Leverage	+		0.0053***	0.0054***	0.0029***	1.15
			(4.04)	(4.31)	(2.46)	
Acc_Quality	+			0.1052**	0.0408	1.70
				(2.18)	(0.82)	
Size	+				0.0008	1.40
					(1.02)	
σ(CFO)	+				0.0154	1.94
					(0.83)	
σ(Sales)	+				0.0173***	1.28
					(2.88)	
Neg_Earn	+				0.0602**	1.73
					(2.09)	
OperCycle	+				0.0010	1.26
					(1.11)	
Year dummies		Yes	Yes	Yes	Yes	
Industry dummies		Yes	Yes	Yes	Yes	
R^2		0.0675	0.1087	0.1124	0.1424	
F-statistics		25.78***	87.750***	23.977***	39.768***	
Adjusted R^2		0.0649	0.1057	0.1093	0.1386	
No. of firms		2009	2009	2009	2009	
(Connected)		(114)	(114)	(114)	(114)	
No. of observations		5717	5717	5717	5717	
(Connected)		(349)	(349)	(349)	(349)	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (one-tailed).
The dependent variable, Fcst_Error, is the absolute value of the difference between the mean forecast and actual EPS scaled by the stock price at the beginning of the fiscal year. See Table 1 for the definitions of explanatory variables used in this table. Year and industry dummies are included in the regression, but are not tabulated. The coefficient estimates are reported. The *t*-values are based on clustered standard errors (Petersen, 2008). The *F*-statistic in Model 1 tests the overall significance of the regression in Model 1. The *F*-statistic in Model 2 examines the incremental contribution of the explanatory variables newly added to Model 1 in Model 2. The *F*-statistic in Model 3 tests the incremental contribution of the explanatory variable(s) newly added to Model 2 in Model 3. The *F*-statistic in Model 4 tests the incremental contribution of the explanatory variable(s) newly added to Model 3 in Model 4.

analyst forecast accuracy when Corrupt equals 0, which is outside the range of observed value for Corrupt (the minimum CPI of 1.7 for Indonesia for 1999 to the maximum of 9.5 for Sweden for 1998 in our sample). Thus the conditional slope of political connection (Polit_Conn) at the mean of Corrupt approximates the general trend in the relationship between political connection and analyst forecast accuracy (Brambor, Clark, & Golder, 2005; Friedrich, 1982).

Nonetheless, the results presented in Table 6 suggest that curbing corruption can directly reduce the forecast error, and effective anti-corruption measures can alleviate the adverse effect of political connections on the forecast accuracy and improve the information environment for investors.

These results provide supporting evidence for our Hypothesis 2 that the impact of political connections is more pronounced in jurisdictions with higher levels of corruption. Collectively they point to the important role that political connections and corruption play in the examination of financial analyst forecast accuracy.

ROBUSTNESS CHECKS

In this section we discuss the results of the robustness tests. To mitigate concerns about the sampling bias effect, we replicate the tests that are reported in Table 6 but exclude all of the UK and US firms, as a disproportionately large number of the connected firms in our sample are from the UK, and a disproportionately small number are from the US. The results (not tabulated, for brevity) for political connection and corruption remain qualitatively similar to those reported in Table 6. The estimated coefficient on the interaction term between these two variables is positive in all four models, but significant only in Models 1, 2, and 3, providing only partial support for Hypothesis 2, which could be due to the substantial reduction in the sample size of connected firms. However, this should not be interpreted as contradictory to our main results, because the findings of subsequent bootstrapping regression analysis, which is adopted specifically for addressing the small sample concern, lend support to all of our hypotheses.

As less than 10% of our sample observations are classified as politically connected, and the reduced sample tests discussed above provide only partial support for Hypothesis 2, the non-proportional sampling effect is cause for some concern. To address this, we test our hypotheses on bootstrapped samples. First, we randomly select 5717 observations with replacements from the sample to construct a random subsample. This random sampling procedure is repeated to produce 1000 such subsamples. Second, each subsample is used in an ordinary least-squares regression analysis to generate a set of estimated coefficients of the variables in the model. Finally, we investigate the distribution of these 1000 individually estimated coefficients for each variable, and determine the significance level by examining the sign of the estimated coefficient at each respective percentile. For example, an estimated coefficient is deemed to be significantly greater than zero at the $p<0.01$ level if its first percentile value is greater than zero, and to be significantly smaller than zero its 99th percentile value is smaller than zero. The bootstrapping results reported in Tables 7 and 8 show that the estimated coefficients of Polit_Conn and its interaction with Corrupt (Polit_Corrupt_C) are in the expected direction and significant at the 1% level throughout Models 1–4 (Tables 5 and 6) for these 1000 regressions. The bootstrapping procedure results are thus consistent with our main results. To further mitigate concern over a non-proportional sample, we also employ matched sample tests in which the connected observations are matched on a one-to-one, one-to-three, and one-to-five basis by country, industry, year, and firm size. The results (not tabulated) remain qualitatively similar to those in Tables 5 and 6.

To determine whether our main results are driven by unidentified factors that are correlated with our classification of political connections, we randomly assign 349 observations as politically connected to match the actual distribution of politically connected observations in our sample by country, by year, and by industry. This process is repeated 1000 times to generate as many random subsamples. We then run 1000 regression analyses using Model 4 reported in Table 6, and sort the 1000 estimated coefficients of each of the experimental variables (Polit_Conn and Polit_Corrupt_C) in ascending order. The results (not tabulated) do not suggest that the results in Table 6 are obtained by chance. Specifically, the value of the estimated coefficient

Table 7 Bootstrapping regression results without the Corrupt variable

Variable	*Pred. sign*	*Mean*	*1%*	*2.5%*	*5%*	*10%*	*Median*	*90%*	*95%*	*97.5%*	*99%*
Polit_Conn											
Model 1	+	0.0214	0.0060	0.0092	0.0107	0.0132	0.0211	0.0302	0.0326	0.0350	0.0377
Model 2	+	0.0288	0.0136	0.0163	0.0184	0.0205	0.0285	0.0374	0.0398	0.0423	0.0446
Model 3	+	0.0284	0.0133	0.0160	0.0180	0.0202	0.0281	0.0372	0.0393	0.0419	0.0442
Model 4	+	0.0294	0.0146	0.0172	0.0192	0.0213	0.0291	0.0380	0.0404	0.0422	0.0451

This table reports the results of bootstrapping regressions by using models reported in Table 5. For brevity, only the estimated coefficients for political connections (Polit_Conn) are reported here. Refer to Table 5 for detailed descriptions of Models 1–4.

Table 8 Bootstrapping regression results with the Corrupt variable and its interaction with the Polit_Conn variable

Variable	*Pred. sign*	*Mean*	*1%*	*2.5%*	*5%*	*10%*	*Median*	*90%*	*95%*	*97.5%*	*99%*
Polit_Conn											
Model 1	+	0.0150	0.0022	0.0043	0.0061	0.0078	0.0148	0.0223	0.0247	0.0269	0.0291
Model 2	+	0.0226	0.0099	0.0121	0.0137	0.0156	0.0224	0.0299	0.0319	0.0341	0.0370
Model 3	+	0.0222	0.0095	0.0116	0.0134	0.0154	0.0220	0.0294	0.0314	0.0337	0.0363
Model 4	+	0.0229	0.0104	0.0122	0.0141	0.0159	0.0228	0.0302	0.0322	0.0336	0.0366
Corrupt											
Model 1	+	0.1244	0.0830	0.0905	0.0950	0.1024	0.1254	0.1445	0.1522	0.1567	0.1649
Model 2	+	0.0979	0.0557	0.0621	0.0674	0.0740	0.0983	0.1207	0.1277	0.1328	0.1424
Model 3	+	0.1048	0.0623	0.0680	0.0739	0.0809	0.1051	0.1278	0.1347	0.1402	0.1501
Model 4	+	0.0989	0.0555	0.0646	0.0687	0.0749	0.0995	0.1229	0.1287	0.1354	0.1466
Polit_Corrupt_C											
Model 1	+	0.1302	0.0020	0.0244	0.0431	0.0647	0.1307	0.1984	0.2148	0.2328	0.2491
Model 2	+	0.1550	0.0271	0.0486	0.0671	0.0900	0.1559	0.2189	0.2388	0.2556	0.2772
Model 3	+	0.1484	0.0216	0.0437	0.0622	0.0826	0.1491	0.2121	0.2321	0.2474	0.2716
Model 4	+	0.1522	0.0288	0.0494	0.0644	0.0872	0.1526	0.2168	0.2346	0.2519	0.2761

This table reports the results of bootstrapping regressions by using models reported in Table 6. For brevity, only the estimated coefficients for three major variables of interest only, political connections (Polit_Conn), corruption (Corrupt), and their interaction term with corruption (Polit_Corrupt_C) are reported here. Refer to Table 6 for detailed descriptions of Models 1–4.

of Polit_Conn is −0.0008 at the 45th percentile, −0.0002 at the 50th percentile, and 0.0005 at the 55th percentile. The values of Polit_Corrupt_C in this range are all negative, which is opposite to the expected sign for these two variables.

We further conduct a Fama–MacBeth (1973) analysis as a sensitivity test to minimize the probability of reporting inflated *t*-values. The average value of the coefficients estimated in five by-year regressions are employed for testing the hypothesized relations. As expected, the results (not tabulated) are qualitatively similar to those reported in Table 6.

We also test whether our results hold qualitatively if political connections are further classified into three categories based on whether the firm is connected to a government official (Gov), to a member of parliament (MP), or indirectly connected to a government official through close friendship or other relations (CR).[20] These three variables (Gov, MP, CR) take the value 1 if the firm is so connected and 0 otherwise. The results (not tabulated) show that the estimated coefficients of Gov and CR are significantly positive, whereas MP is not, suggesting that only connections with government officials generate significant political benefits for the firm.

To examine the sensitivity of our results to national cultural differences that may affect the political process (DiRienzo et al., 2007), we add the variable Culture to our model, which is defined as the first principal component of the power distance index, individualism, masculinity, and the uncertainty avoidance index as identified by Hofstede (2001). The results (not tabulated) indicate that the inclusion of this variable does not change our results qualitatively, as Polit_Conn remains significantly positive. In addition, both Corrupt and its interaction with Polit_Conn continue to be significantly positive.

As an additional robustness check we controlled for six national-level competitiveness factors from the *World competitiveness yearbook* (IMD, 2009): *capital markets*, *justice*, *competent senior managers*, *finance and banking regulation*, *shareholders' right* and *financial institutions' transparency*. Our main results (not tabulated) remain qualitatively unchanged.

Finally, we perform a Heckman (1976) test to see whether our results are sensitive to control for possible self-selection bias. In the first stage of the regression, a Probit model is used to estimate the probability of having political connections based on whether a firm is located in the capital city of a country, where it is assumed that establishing political connections is more likely to occur (Bertrand, Kramarz, Schoar, & Thesmar, 2004; Siegel, 2005). In the second stage, this estimated value (Est. Polit_Conn) is used to replace the variable Polit_Conn, and an additional control variable Lamda is added to the model to correct any self-selection bias. The value of Lamda is calculated by using the probability densities derived from the first-stage Probit model.[21] Again, our main results remain qualitatively unchanged in the Heckman model (not tabulated). These sensitivity test results thus indicate that our main findings are not likely to be driven by sampling or statistical bias.

SUMMARY AND CONCLUSION

Corporate political connections have been a topical research issue since the recent publication of several important studies on the matter (Faccio, 2006, 2009; Faccio & Masulis, 2005; Faccio & Parsley, 2006; Leuz & Oberholzer-Gee, 2006). We argue that the often unexpected benefits of political connections complicate the earnings generation process, which makes the task of forecasting earnings more difficult. Forecast accuracy is thus predicted to be negatively associated with political connections. After controlling for factors identified by previous studies as affecting forecast accuracy, we find that analyst forecasts are less accurate for politically connected firms than for non-connected firms. These results suggest that future IB research in this area should view political connections as an important source of influence for analyst forecast outcomes.

The more interesting result of our study is that host-country corruption level largely explains the adverse effect of political connections on analyst forecast accuracy. This explanation is consistent with our argument that the net benefit of political connections is reduced by anti-corruption efforts, which are accompanied by more effective enforcement of law and more developed market mechanisms that serve to set boundaries for the nepotism of politicians. However, we believe that the adverse effect of political connections on analyst forecast accuracy in regimes where corruption is common remains a vital issue for international investors, as capital has increasingly flowed into emerging markets where corruption creates more opportunities for politicians to expropriate business transactions.

Shaffer (1995) and Hillman, Keim, and Schuler (2004) review recent developments in political science, political economy, sociology, economics, finance and management that are relevant to IB studies, and find that more research efforts are needed to understand the effect of politics and corruption in the context of IB. This study is a timely response to the call, and its findings provide fresh evidence that serves as a stepping stone for further investigation in this area.

First, by studying the relationship between political connections and analyst forecasts, this study offers insights into how politics may affect the information environment, as the literature shows that factors related to the informational environment affect investor decisions (Agarwal & Feils, 2007; Davis, Desai, & Francis, 2000; Globerman & Shapiro, 2003). Hillman and Wan (2005) find that MNE subsidiaries adopt political strategies to achieve both internal legitimacy (pressures from the parent company) and external legitimacy (social and political pressures from the host country). Attributes of financial analyst forecasts are often employed to proxy for the informational environment. Our findings shed light on the relationship between the forecast errors of financial analysts and corporate political connections – an important and hitherto unresolved research issue for IB scholars.

Second, our study demonstrates how host-country corruption level can affect the impacts of political influence in an international setting, which adds to a large body of related IB literature. Habib and Zurawicki (2002) find that both the absolute level of corruption in the host country and the difference in corruption level between the home and the host country deter FDI. They argue that investors tend to avoid corruption not only because it is considered morally unacceptable, but also because it reduces operational efficiency. In the same vein, Zhao, Kim, and Du (2003) show that the presence of high corruption and low transparency significantly hinders the inflow of FDI to host countries. In a reversed direction, Robertson and Watson (2004) find that a large increase in FDI flowing into a country results in a higher level of corruption, because the new FDI inflow represents eagerness on the part of foreign firms and so expands the opportunities for bribery. However, DiRienzo et al. (2007) show that the greater the access to information, the lower the level of corruption. Although portfolio diversification has been identified as a major factor in determining the cross-border flow of funds (Zhao, 2008), distance in space or culture heightens international investors' need for information. Our findings extend this strand of MNE literature by improving the understanding of the effect of interaction between corporate political connections and corruption on the information environment in the host country.

The findings of this study pose practical and challenging tasks for IB practitioners. First, at the firm level, knowledge of earnings properties and their variation due to political connections should help investors to improve their portfolio management. The difficulty in forecasting earnings of politically connected firms implies that, before making foreign investment decisions, investors must examine whether the target firm is politically connected, and if it is, they should be aware of the additional information asymmetry about the target firm and carefully evaluate the government apparatus and operations resulting from political connections and their direct and indirect impacts on the firm's future performance and risk. Second, at the country level, the exacerbating effect of corruption on the adverse impacts of political influence implies that investors should differentiate target firms with political connections in countries with higher levels of corruption from those in countries with more developed institutions that can counter corruptive forces. Investors can expect to benefit from their extra efforts in gathering and analyzing such information before investing in a politically connected firm.

Nevertheless, despite its merits, this study is not without limitations. Our sample of politically connected firms is relatively small, although we do make extensive efforts, including matched sample tests and bootstrapping estimations, to counter concerns on this front. As politically connected firms represent the minority of firms in all parts of the world, this sampling issue should not distract from our main findings. Another limitation, and one that points to possible future research directions, is that this study focuses on the differential effect of corruption on corporate political connections across countries, yet there are a host of other institutional factors that could also affect the costs and benefits of maintaining relations with politicians. Future research that explores the effect of alternative institutional factors and compares them with the influence of corruption is thus warranted to fine-tune our understanding in this field.

ACKNOWLEDGEMENTS

The authors thank Mara Faccio for providing the data on political connections for this study. We are deeply indebted to the editor, Lee Radebaugh, and to two anonymous reviewers for their insightful comments and suggestions. We also thank T. J. Wong, Joseph Fan, Joe Weintrop, Bin Ke, Steven Lim, and workshop participants at the Chinese University of Hong Kong, Seoul National University, the 13th Annual Mid-Year Conference of the International Accounting Section of the American Accounting Association, research seminars at the Turku School of Economics, Finland, the China Europe International Business School, China, the University Montesquieu Bordeaux 4, France, and the HEC School of Management, Paris, France, for their helpful comments and advice. Charles Chen and Yuan Ding acknowledge the financial support of Procore-France and the Hong Kong Joint Research Scheme. Yuan Ding gratefully acknowledges the generous support of Jiangsu Jinsheng Industry Co., Ltd. Francis Kim acknowledges the financial support from City University of Hong Kong (Project No. 7002256). We thank Ching-Tung Yu for extensive research assistance.

NOTES

[1]Focusing on high-profile politicians may underestimate the effect of political connections, because less visible connections may be overlooked. We address this issue in the section on robustness checks.

[2]One may maintain that managers of connected firms are unlikely to have strong incentives to smooth earnings, because their jobs are better secured by their connections, and they are less likely to raise capital from the public (Chaney et al., 2007).

[3]Kobrin (1979) provides a detailed review of early studies on this issue.

[4]One may contend that investor demand for information motivates analysts to compete in learning to forecast the effect of political outcomes on future earnings, and thus that some analysts may forecast the earnings of connected firms better than others. However, the inherently complex nature of political maneuvers renders their efforts less fruitful, and on average, analysts can be expected to be less capable of forecasting the earnings of politically connected firms.

[5]See the Italian "football savior" law example above.

[6]For example, under the Nazi regime, German armament producers worked through the National Socialist German Workers' Party to expand their access to the domestic market (Ferguson & Voth, 2008). Brazilian firms that had contributed substantially to political campaigns increased their bank leverage after each election, indicating that access to bank finance is an important channel through which political connections operate (Claessens et al., 2008). In Indonesia,

during the Suharto era, the London-based Thames Water Overseas Ltd formed an alliance with Suharto's son, Sigit Harjojudanto, who had no previous experience in the water business. In exchange for the business access that Sigit brought to the firm, Thames granted him 20% ownership of the joint business venture (Purbasari & Mobarak, 2007).

[7]It may be contended that firms with political connections are associated with *more* accurate analyst earnings forecasts. This is more common in countries with transparent economies (Faccio, 2006). Faccio (2006) suggests that transparent economies are better able to tolerate corporate political connections, because any misuse would be more likely to be detected. However, whether country-level variation in the transparency of the economic system leads to firm-level transparency is an empirical question.

[8]"Connections of this type occur when a person who was a head of state or prime minister between 1997 and 2001 (or one of their relatives) was also a top executive or a large shareholder of the company during 1997 or 2001 (except for the cases that fall into the paragraph directly above); when a government minister or a member of parliament as of 2001 was a top executive or a large shareholder of the company during 1997; when a large shareholder or a top officer is a friend of a minister or MP; when a large shareholder or a top officer is a politician in another country; or when a large shareholder or a top officer is known to be associated with a political party" (Faccio, 2006: 371).

[9]For details of the CPI, please refer to the Transparency International Website: www.transparency.org.

[10]Forecast optimism and forecast dispersion were also examined in an early version of this study, and the results indicated that political connections are associated with more optimistic and more dispersed forecasts.

[11]We also use the squared difference between the forecast and actual earnings, scaled by the stock price at time $t-1$, assuming that analysts face a quadratic loss function, and the results (not tabulated) remain qualitatively similar. Using the absolute value of the difference assumes that analysts face a linear loss function, and hence try to minimize their absolute forecast error.

[12]We also use analyst forecasts separately compiled by IBES 8 months, 7 months, and 6 months before the fiscal year-end to obtain similar cut-off dates for forecasts. The results using forecasts issued by individual months maintain the same tenor as those reported in this paper.

[13]Firm size also controls for differences in the information environment, as large firms tend to attract more public attention and media coverage. In our study, size is measured as the natural log of total assets, but our results are qualitatively equivalent when other measures of size, such as net sales and the market value of equity capital, are used.

[14]We assume that each analyst has a similar forecasting ability, and consequently do not control for analyst experience, the size of the employer, or the number of firms and industries covered. We acknowledge that analyst characteristics may affect forecasting performance (Clement & Tse, 2005; Hong & Kubik, 2003). However, the differential forecasting abilities of analysts should be biased against finding significant results in this study, because our sample indicates that connected firms are larger and attract more analyst coverage.

[15]We use the Fama–French 48-industry classification (Fama & French, 1997).

[16]In Panel A of Table 2, Indonesia, Italy, and Korea appear as outliers in their CPI levels. In an unreported robustness check, our results remain unchanged after dropping the observations from these countries.

[17]As a result of our focus on high-level political connections, there is only one connected firm in the defense industry in our sample, which is consistent with the results reported by Faccio (2006). For a robustness check we broaden the definition of political connection by following Goldman, Rocholl, and So (2009), which includes an examination of all members of the board of directors, and classifies a firm as connected if any one member of the board is politically connected. However, we ended up with only one firm (Lockheed Martin) with political connection in the US defense industry. Since hand-collecting related information may result in a less verifiable sample that would require attestation of its reliability and data integrity from an independent source, we limit this test to only pharmaceutical and petroleum industries in the US. Our results remain qualitatively unchanged.

[18]The VIF values are reported in all regression tables, and none of them exceeds the value of 2.

[19]We also conduct Fama–MacBeth regression in the robustness check section to correct the cross-sectional correlation problems.

[20]The classification is based on additional information generously provided by Mara Faccio during the revision process for this paper.

[21]See Heckman (1976) for a detailed discussion of this procedure.

REFERENCES

Agarwal, J., & Feils, D. 2007. Political risk and the internationalization of firms: An empirical study of Canadian-based export and FDI firms. *Canadian Journal of Administrative Sciences*, 24(3): 165–181.

Barth, M. E., Kasznik, R., & McNichols, M. F. 2001. Analyst coverage and intangible assets. *Journal of Accounting Research*, 39(1): 1–34.

Bertrand, M., Kramarz, F., Schoar, A., & Thesmar, D. 2004. *Politically connected CEOs and corporate outcomes: Evidence from France*, Working Paper, University of Chicago and MIT.

Bhattacharya, U., Daouk, H., & Welker, M. 2003. The world price of earning opacity. *Accounting Review*, 78(3): 641–678.

Boddewyn, J. J. 1988. Political aspects of MNE theory. *Journal of International Business Studies*, 19(3): 341–363.

Brambor, T., Clark, W. R., & Golder, M. 2005. Understanding interaction models: Improving empirical analyses. *Political Analysis*, 14(1): 63–82.

Brown, L. D. 1993. Earnings forecasting research: Its implications for capital markets research. *International Journal of Forecasting*, 9(3): 295–320.

Chaney, P. K., Faccio, M., & Parsley, D. C. 2007. *The quality of accounting information in politically connected firms*, SSRN Working Paper, http://ssrn.com/abstract=966379.

Claessens, S., Feijen, E., & Laeven, L. 2008. Political connections and preferential access to finance: The role of campaign contributions. *Journal of Financial Economics*, 88(3): 554–580.

Clarke, J., & Subramanian, A. 2006. Dynamic forecasting behavior by analysts: Theory and evidence. *Journal of Financial Economics*, 80(1): 81–113.

Clement, M. B., & Tse, S. Y. 2005. Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, 60(1): 307–341.

Crispin, S. W. 2002. Political connections. *Far Eastern Economic Review*, 165(21): 33.

Cuervo-Cazurra, A. 2006. Who cares about corruption? *Journal of International Business Studies*, 37(6): 807–822.

Davis, B. 2001. Chairman's deep political connections run silent. *Wall Street Journal Eastern Edition*, 238: A10.

Davis, P. S., Desai, A. B., & Francis, J. D. 2000. Mode of international entry: An isomorphism perspective. *Journal of International Business Studies*, 31(2): 239–258.

Dechow, P. M., & Dichev, I. D. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *Accounting Review*, 77(Supplement): 35–59.

DiRienzo, C. E., Das, J., Cort, K. T., & Burbridge Jr., J. 2007. Corruption and the role of information. *Journal of International Business Studies*, 38(2): 320–332.

Duru, A., & Reeb, D. M. 2002. International diversification and analysts' forecast accuracy and bias. *Accounting Review*, 77(2): 415–433.

Faccio, M. 2006. Politically connected firms. *American Economic Review*, 96(1): 369–386.

Faccio, M. 2009. *Differences between politically connected and non-connected firms: A cross country analysis*, SSRN Working Paper, http://ssrn.com/abstract=918244.

Faccio, M., & Masulis, R. W. 2005. The choice of payment method in European mergers and acquisitions. *Journal of Finance*, 60(3): 1345–1388.

Faccio, M., & Parsley, D. C. 2006. *Sudden deaths: Taking stock of geographic ties*, ECGI – Finance Working Paper No. 113/2006, http://ssrn.com/abstract=875808.

Faccio, M., Masulis, R. W., & McConnell, J. J. 2006. Political connections and corporate bailouts. *Journal of Finance*, 61(6): 2597–2635.

Fama, E. F., & French, K. R. 1997. Industry costs of equity. *Journal of Financial Economics*, 43(2): 153–193.

Fama, E. F., & MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3): 607–636.

Ferguson, T., & Voth, H. 2008. Betting on Hitler: The value of political connections in Nazi Germany. *Quarterly Journal of Economics*, 33(1): 101–137.

Fisman, R. 2001. Estimating the value of political connections. *American Economic Review*, 91(4): 1095–1102.

Francis, J., LaFond, R., Olsson, P. M., & Schipper, K. 2004. Costs of equity and earnings attributes. *Accounting Review*, 79(4): 967–1010.

Friedrich, R. J. 1982. In defense of multiplicative terms in multiple regression equations. *American Journal of Political Science*, 26(4): 797–833.

Globerman, S., & Shapiro, D. 2003. Governance infrastructure and US foreign direct investment. *Journal of International Business Studies*, 34(1): 19–39.

Goldman, E., Rocholl, J., & So, J. 2009. Do politically connected boards affect firm value? *Review of Financial Studies*, 22(6): 2331–2360.

Habib, M., & Zurawicki, L. 2002. Corruption and foreign direct investment. *Journal of International Business Studies*, 33(2): 291–307.

Heckman, J. 1976. The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement*, 5: 475–492.

Hillman, A., Keim, G., & Schuler, D. 2004. Corporate political activity: A review and research agenda. *Journal of Management*, 30(6): 837–857.

Hillman, A., & Wan, W. 2005. The determinants of MNE subsidiaries' political strategies: Evidence of institutional duality. *Journal of International Business Studies*, 36(3): 322–340.

Hillman, A., Zardkoohi, A., & Bierman, L. 1999. Corporate political strategies and firm performance: Indications of firm-specific benefits from personal service in the US government. *Strategic Management Journal*, 20(1): 67–81.

Hofstede, G. 2001. *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations*, (2nd ed.) London: Sage Publications.

Hong, H., & Kubik, J. D. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance*, 58(1): 313–351.

Hope, O. 2003. Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research*, 41(2): 235–272.

Hunt, A. R. 2002. A scandal centerpiece: Enron's political connections. *Wall Street Journal Eastern Edition*, 239: A15.

IMD. 2009. *World competitiveness yearbook*. www.imd.ch/wcy/.

Jackson, G., & Deeg, R. 2008. Comparing capitalisms: Understanding institutional diversity and its implications for international business. *Journal of International Business Studies*, 39(4): 540–561.

Jaccard, J., Wan, C. W., & Turrisi, R. 1990. The detection and interpretation of interaction effects between continuous variables in multiple regression. *Multivariate Behavior Research*, 25(4): 467–478.

Kapner, F. 2003. Italy's "savior" laws face probes. *Financial Times*, 4 November: 26.

Kobrin, S. J. 1979. Political risk: A review and reconsideration. *Journal of International Business Studies*, 10(1): 67–80.

Krishnaswami, S., & Subramaniam, V. 1999. Information asymmetry, valuation, and the corporate spin-off decision. *Journal of Financial Economics*, 53(1): 73–112.

Krueger, A. O. 1974. The political economy of the rent-seeking society. *American Economic Review*, 64(3): 291–303.

LaPalombara, J. 1994. Structural and institutional aspects of corruption. *Social Research*, 61(2): 325–350.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. 1998. Law and finance. *Journal of Political Economy*, 106(6): 1113–1155.

Leuz, C., & Oberholzer-Gee, F. 2006. Political relationships, global financing, and corporate transparency: Evidence from Indonesia. *Journal of Financial Economics*, 81(2): 411–439.

Petersen, M. A. 2008. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1): 435–480.
Purbasari, D. P., & Mobarak, A. M. 2007. *Do multinational corporations seek out politically connected firms? Evidence on local partner search by MNCs in Indonesia*, Working Paper, University of Colorado at Boulder.
Roberts, B. E. 1990. A dead senator tells no lies: Seniority and the distribution of federal benefits. *American Journal of Political Science*, 34(1): 31–58.
Robertson, C., & Watson, A. 2004. Corruption and change: The impact of foreign direct investment. *Strategic Management Journal*, 25(4): 385–396.
Rodriguez, P., Siegel, D. S., Hillman, A., & Eden, L. 2006. Three lenses on the multinational enterprise: Politics, corruption, and corporate social responsibility. *Journal of International Business Studies*, 37(6): 733–746.
Shaffer, B. 1995. Firm-level responses to government regulation: Theoretical and research approaches. *Journal of Management*, 21(3): 495–514.
Siegel, J. 2005. *Contingent political capital and international alliances: Evidence from South Korea*, Working Paper, Harvard Business School.
Simon, J. A. 1984. A theoretical perspective on political risk. *Journal of International Business Studies*, 15(3): 123–143.
Smith, K. W., & Sasaki, M. S. 1979. Decreasing multicollinearity: A method for models with multiplicative functions. *Sociological Methods & Research*, 8(1): 35–56.
Smith-Hillman, A. V., & Omar, M. 2005. FDI, international business and regulation: The behaviour of UK multinational corporations. *European Business Review*, 17(1): 69–82.
Stigler, G. J. 1971. The theory of economic regulation. *Bell Journal of Economics and Management Science*, 2(1): 3–21.
Tanzi, V. 1998. *Corruption around the world: Causes, consequences, scope, and cures*, IMF Working Paper WP/98/63, International Monetary Fund, Washington, DC.
Zhao, H., Kim, S., & Du, J. 2003. Corruption, transparency and foreign direct investment: A cross-country analysis. *Management International Review*, 43(1): 41–63.
Zhao, X. 2008. Determinants of flows into retail international equity funds. *Journal of International Business Studies*, 39(7): 1169–1177.

ABOUT THE AUTHORS

Charles JP Chen is a professor of Accounting at the China Europe International Business School (CEIBS). He received his PhD in accounting from University of Houston (University Park). His current research interests include issues related to international accounting harmonization, financial analyst forecasts, auditing, accounting issues in China, and corporate governance. Born in China, he is a citizen of the People's Republic of China. His e-mail address is ccharles@ceibs.edu.

Yuan Ding is a professor of Accounting at the China Europe International Business School (CEIBS). He received his PhD in accounting from the University Montesquieu Bordeaux IV, France. His current research is focused on intangibles, international accounting harmonization, earnings management, analyst forecasts, corporate governance issues, and accounting reform in China. Yuan Ding was born in China and is a French citizen. His e-mail address is dyuan@ceibs.edu.

Chansog (Francis) Kim is an associate professor in the Department of Accountancy, College of Business, City University of Hong Kong. He received his PhD from Baruch College of City University of New York. His current research interests include security analyst forecasting behaviors, capital market-based accounting research, and auditing. He was born in Korea and is a Korean citizen. His e-mail address is acckim@cityu.edu.hk.

Accepted by Lee Radebaugh, Area Editor, 12 February 2010. This paper has been with the authors for three revisions.