DEPARTMENT OF MANAGEMENT

BOARD INDEPENDENCE, CEO DUALITY AND FIRM PERFORMANCE

A QUANTILE REGRESSION ANALYSIS FOR INDONESIA, MALAYSIA, SOUTH KOREA AND THAILAND

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Board Independence, CEO Duality and Firm Performance

A Quantile Regression Analysis for Indonesia, Malaysia, South Korea and Thailand

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Abstract

We study the effect of board independence and CEO duality on firm performance for a sample of stock-listed enterprises from Indonesia, Malaysia, South Korea and Thailand, applying Quantile Regression. Quantile Regression is more powerful than standard linear regression, as reflected in the Ordinary Least Square (OLS) regression method, since Quantile Regression can produce estimates for all conditional quantiles of the distribution of a response variable, whereas OLS regression only estimates the conditional mean effects of a response variable. Moreover, Quantile Regression is better able to handle violations of the standard assumptions of normality, homoscedasticity and absence of outliers. Indeed, we find that the relationship between corporate governance and firm performance variables is different across the conditional quantiles of the distribution of firm performance, something OLS would leave unidentified. This finding suggests that estimating the quantile effect of a response variable can well be more insightful than estimating only the mean effect of this response variable, particularly so when the data violate assumptions required to perform OLS regression, as is often the case in corporate governance research.

1. Introduction

In the organization sciences' literature, many issues remain unsolved empirically because different studies report different results. In many topical domains, some studies report significantly negative relationships, others significantly positive ones, and yet others insignificant ones. Yet others complicate matters by adding non-linearities, finding U-shaped or reversed U-shaped linkages with or without the reflection point being located within the observed range, or by including all kinds of intermediating or moderating effects. A well-known example of a literature revealing such a state of the art is the one on the corporate diversification – performance link in strategic management. Of course, many reasons may explain such a mixed bag of findings, obvious candidates being different samples and different specifications across studies. However, we believe that often such empirical inclusiveness may, in part, be explained by the dominant estimation method applied, being standard Ordinary Least Squares (OLS) linear regression or offsprings thereof.

In the board composition and board leadership structure literature, the current state of the art is not very different. These two corporate governance mechanisms and their links to firm performance are hotly debated in the economics, finance, and organization sciences literatures, both at the theoretical and empirical level, with the evidence reflecting a mixed bag of findings. On theoretical level, two main theories, agency theory and stewardship theory, have their own arguments in explaining the link between board composition (and board leadership structure) and firm performance. From an agency theory perspective, on the one hand, a supervisory board should be dominated by independent non-executive members in order to generate effective monitoring of executives. Moreover, the CEO and board chairman should be different people in order to clearly separate operational from control responsibilities. However, from a stewardship theory perspective, on the other hand, board composition should be dominated by inside members in order to make effective decisions, since insiders are better informed about the firm than outside directors. Additionally, this perspective argues that the CEO and board chairman position should be in one hand (CEO duality), rather than to be separated into two positions (CEO non-duality), because this facilitates clear and strong leadership. The contradictory predictions from theory are mirrored in the available evidence. Some studies found evidence that supports agency theory, and some others revealed evidence in support of stewardship theory. So, no convincing conclusion can be drawn from prior studies on the impact of board composition and board leadership on firm performance (see, for example, Dalton, Daily, Ellstrand and Johnson, 1998, for a meta-analytic review).

In theoretical and empirical work, several efforts have been carried out to consolidate the debate on the effectiveness of these two corporate governance mechanisms, and to reconcile seemingly conflicting evidence. On the theoretical front, Aguilera, Filatotchev, Gospel and Jackson (2008) argue that the effectiveness of corporate governance mechanisms depends on critical environmental variables. Implementation of these mechanisms does not only produce benefits, but also implies that costs have to be incurred. Both the benefits and costs tend to vary with specific environmental variables. Consequently, the mixed evidence mirrors the variety of external conditions that can be found in the world of businesses. An earlier study of Demsetz (1983) provides another theoretical reason for the observed ambiguity. He argues that the adoption of corporate governance devices is as an endogenous outcome of a maximizing process, as firms search for an optimal equilibrium in the face of the advantages and disadvantages of such devices. Therefore, firm heterogeneity may imply different corporate governance choices, which explain why the impact of corporate governance variables on firm performance varies from one study to the other. In a similar vein, Hermalin and Weisbach (2003), focusing on the board of directors, argue that corporate governance mechanisms are endogenously determined in the context of the system of board characteristics, board action, and firm performance. As a result, they argue, the direct relationship between any board characteristic and firm performance may be spurious. Davis, Schoorman and Donaldson (1997) reconcile the different predictions of agency and stewardship theory by identifying psychological attributes and situational characteristics that indicate under what conditions agency theory or stewardship theory is likely to hold.

On the empirical front, Boyd (1995) develops a contingency model to explain the mixed bag of results. He argues that the sign and magnitude of the CEO duality–firm performance relationship vary systematically across the environmental conditions of munificence, complexity and dynamism. Elsayed (2007) explains the mixed results in CEO duality-performance literature by arguing that the direction and magnitude of this link are different across industries. Black, Jang and Kim (2006) refer to the logic that corporate governance implementation can be a signal of the quality of the firm, to then argue why regression with instrumental variables is needed to address this endogeneity issue. After all, high-performing stock-listed firms may adopt good corporate governance practices to signal that their firms' insiders behave well – that is, in the interest of shareholders.

The current study is aimed at empirically exploring an alternative way to reconcile the mixed bag of findings as to the firm performance effect of CEO duality and board independence by applying the method of Quantile Regression. This method offers an alternative approach to identify the mixture of relationships that might be hidden in data that fail to satisfy one or more of the assumptions associated with standard OLS regression, as employed in almost all prior studies on corporate governance. Quantile Regression is designed to estimate the relationship of explanatory variables at different points (i.e., quantiles) in the conditional distribution of the dependent variable. By using this regression method, a complete picture can be derived of how our pair of corporate governance mechanisms relates to firm performance at different conditional quantiles. By applying Quantile Regression, therefore, we can address the question as to whether the sign and/or magnitude of the corporate governance – firm performance relation are different for different levels of firm performance: is this relationship different for, say, high vis-à-vis low-performing enterprises? Classical linear regression only estimates the relationship between two or more variables for the conditional mean – here, of firm performance. Below, we will explain this in greater detail.

So, in this study, we contribute to the debate by suggesting Quantile Regression as an advanced estimation method in the corporate governance literature, arguing that this can be instrumental in reconciling the seemingly conflicting findings from studies applying OLS regression and its many offsprings. Specifically, we expect that the relationship between board independence and CEO duality, on the one hand, and firm performance, on the other hand, may well be different across performance quantiles. Additionally, we offer fresh evidence for four understudied countries: Indonesia, Malaysia, South Korea and Thailand. Moreover, in the conclusion, we will argue that Quantile Regression is widely applicable in the organization sciences.

Hence, this paper offers a methodological and a substantive contribution, by both introducing a method new to the organization sciences and by applying this method to the corporate governance – firm performance relationship. Below, we first offer a brief overview of the state of the art in corporate governance research on board independence and CEO duality. Next, we describe what Quantile Regression is, in theory, and how the method works, in practice. Subsequently, we introduce our data. After that, we demonstrate the application of this regression method in the context of the relationship between corporate governance and firm performance. Finally, we conclude with a discussion.

2. Board Independence and CEO Duality

In the corporate governance literature, theoretical and empirical debates abound on the effectiveness of specific structures of (non-)executive boards. The conflicting predictions of agency theory vis-à-vis stewardship theory as to the effectiveness of independent directors – or board independence – reflect one of these debates. On the one hand, agency theory argues that a larger proportion of independent directors will promote better firm performance. This theory assumes that managers are individualistic, opportunistic and self-serving. Then, effective monitoring by independent boards is a key to make executives effectively pursue shareholder rather than self-interests. The (often implicit) assumption is that independent directors are not hindered by tendencies to pursue private interests. Consequently, boards with more independent directors can perform managerial monitoring tasks more effectively (Eisenhardt, 1989; Fama and Jensen, 1983; Fama, 1980; Jensen and Meckling, 1976). On the other hand, stewardship theory argues that boards dominated by insiders are to be preferred to boards dominated by outsiders as managers are assumed to be collectivistically and pro-organizational oriented, as well as trustworthy. An additional argument is that inside directors are better informed about their firms, which makes them better able to support effective decision-making than independent directors. Stewardship theory assumes that managers are good stewards of corporations by acting in the best interests of their principals. As a result, this theory predicts that insider-dominated boards will boost firm performance (Davis, Schoorman and Donaldson, 1997; Donaldson and Davis, 1991, 1994; Donaldson, 1990).

This state of the art in the theoretical arena is mirrored in empirical work on the board independence – firm performance link. The meta-analytic study of Dalton, Daily, Ellstrand and Johnson (1998) clearly reveals the mixed findings on the relationship between board independence (and CEO duality) and firm performance. They conclude that "neither board composition [proportion of independent directors] nor board leadership structure [CEO duality] has been consistently linked to firm performance" (1998: 269). Table 1 presents a summary of the studies on the relationship between board independence and firm performance.

[Insert Table 1 about here]

We can see that the evidence on this relationship is mixed indeed. Some studies support agency theory (Coles, Daniel and Naveen, 2008; Cho and Kim, 2007; Klein, 1998; Daily and Dalton, 1993; Ezzamel and Watson, 1993; Daily and Dalton, 1992; Pearce and Zahra, 1992; Rosenstein and Wyatt, 1990; Schellenger, Wood and Tashakori, 1989; Kesner, 1987; Baysinger and Butler, 1985), others provide evidence for stewardship theory (Cornett, 2008; Kiel and Nicholson, 2003; Bhagat and Black, 2002; Klein, 1998; Agrawal and Knoeber, 1996; Yermack, 1996; Kesner, 1987), and yet others go against both theories (Al Farooque, van Zijl, Dunstan and Karim, 2007; Ghosh, 2006; Cheung, Raub and Stouraitis, 2006; Kesner, Victor and Lamont, 1986; Chaganti, Mahajan and Sharma, 1985).

Some possible explanations of these mixed findings might be related to samples that come from different institutional environments (Aguilera, Filatotchev, Gospel and Jackson, 2008) and different industries (Elsayed, 2007), as well as the different psychological attributes of the managers and the different characteristics of the organizations (Davis, Schoorman and Donaldson, 1997). Additionally, Table 1 reveals that prior studies employed standard linear regression methods such as OLS, WLS, 2SLS or panel data regression. These standard linear regression methods implicitly estimate the conditional mean of the relationship between the variables of interest. So, the interpretation of the relationship between the variables of interest in earlier work should be limited to this relationship at the conditional mean. This is not different for the studies using ANOVA or MANOVA techniques, which only imply a comparison at the mean, too.

So, the literature review indicates that, both on theoretical and empirical grounds, a clear and unambiguous prediction as to the effect of the proportion of independent board members on firm performance is difficult to make. For that reason, we derive two opposing hypotheses as our benchmarks – an H1 on the basis of agency theory, and an H1Alt from stewardship theory.

H1: *Board independence is positively associated with firm performance.*

H1Alt: *Board independence is negatively associated with firm performance.*

A similar theoretical debate between agency theory and stewardship theory revolves around the issue of the effectiveness of CEO duality (whether or not the CEO and chairman of the board is the same person) as a governance mechanism. As with board independence, agency theory and stewardship theory are associated with opposite predictions as to the effectiveness of CEO duality as a governance mechanism. On the one hand, agency theory argues that personal separation of the CEO and chairman roles (CEO non-duality) is important to develop effective monitoring by the board. If the CEO and chairman of the board is the same person, agency theory argues that this is likely to create abuse of power, since this person will be very powerful without effective checks and balances to control her or him. Consequently, agency theory predicts that firms with separation of the CEO and the chair of the board – i.e., CEO non-duality – perform better than their counterparts without separation – i.e., CEO duality (Finkelstein and D’Aveni, 1994; Fama and Jensen, 1983). On the other hand, stewardship theory argues that putting the roles of CEO and chairman of the board in a single hand (CEO duality) is essential to unify and to remove ambiguity from firm leadership. According to stewardship theory, when the roles of CEO and chairman of the board are performed by different people, they often have contrary objectives (see, for example, Dalton, Daily, Ellstrand and Johnson, 1998, for a meta-analysis). So, stewardship theory predicts that firms with CEO duality perform better than firms without such duality.

Again, this theoretical state of the art is reflected in empirical work. Jointly, previous studies have produced mixed results as to the sign of the relationship between CEO duality and firm performance. Table 2 provides a summary of prior studies on this relationship.

[Insert Table 2 about here]

As above, some studies support agency theory (Kiel and Nicholson, 2003; Pi and Timme, 1993; Rechner and Dalton, 1991), others provide evidence for stewardship theory (Cornett, 2008; Donaldson and Davis, 1991), and yet others fail to support either theory (Elsayed, 2007; Al Farooque, van Zijl, Dunstan and Karim, 2007; Cheung, Raub and Stouraitis, 2006; Baliga, Moyer and Rao, 1996; Daily and Dalton, 1993; Daily and Dalton, 1992; Daily and Dalton, 1992; Kesner, Victor and Lamont, 1986; Chaganti, Mahajan and Sharma, 1985).

Similar to the ambiguity in the literature on the relationship between board independence and firm performance, the mixed evidence can be explained with reference to differences across samples, such as different munificence, complexity and dynamism of the environment (Boyd, 1995), or different industries (Elsayed, 2007). And again, different attributes of the managers and different characteristics of the organizations may contribute to the ‘mixed bag’ explanation (Davis, Schoorman and Donaldson, 1997). Also, the estimation methods used in empirical work tend to be from the standard linear regression family, such as OLS, 2SLS and panel data regression techniques. Therefore, findings from prior studies have to be interpreted as the outcomes from estimates of the relationship on the conditional mean only.

Again, from the above, we derive two opposing hypotheses as our benchmarks in this study – an H2 on the basis of agency theory, and an H2Alt from stewardship theory.

H2: *CEO duality is negatively associated with firm performance.*

H2Alt: *CEO duality is positively associated with firm performance.*

3. How does Quantile Regression work?

For the sake of parsimony, we refer below to OLS regression as our benchmark case, without any loss of generality. Quantile Regression has been widely applied in different literatures outside the organization sciences, generally, and corporate governance, particularly. Illustrative examples are Maning, Blumberg and Moulton (1995) and Goel and Ram (2004) in elasticity of demand work, Eide and Mark (1998), Arias, Hallock and Escudero (2001) and Buchinsky (2001) in education economics, Barreto and Hughes (2004) in economic growth studies, Buchinsky (1994), García, Hernández and Nicholás (2001), Machado and Mata (2001) and Nielsen and Rosholm (2001) in wage analysis, Ribeiro (2001) in labor economics, Abrevaya (2001) in population economics, Bassett Jr and Chen (2001) in portfolio investment research, and Cade, Terrell and Schroeder (1999) and Knight and Ackerly (2002) in ecology science.

Quantile Regression is more powerful than the standard linear OLS regression by producing separate estimates for all conditional quantiles of a response variable's distribution. This is different from OLS regression, which estimates only a conditional mean effect of a response variable. Quantile Regression works well under assumptions more relaxed than those associated with OLS regression, being able to handle skewed data, unequal variance (heteroscedasticity) and existence of outliers. OLS regression estimates the conditional mean of a response variable, implying that this regression gives the estimated mean of a response variable for each value of the explanatory variables. Since OLS estimates the mean of a response variable, the distribution of this response variable's data should be normal, which implies a symmetric and bell-shaped distribution with thin tails, in order to produce linear, unbiased and efficient estimators (Johnston and DiNando, 1997).

More generally, strict assumptions as to normality, homoscedasticity and absence of outliers should be fulfilled to perform OLS regression. First, the normality assumption is important to ensure that the mean represents a central tendency of the response variable, given each value of the explanatory variables. A normal distribution also guarantees that the mean coincides with both the median and mode. Normality in the data can ensure that the error terms are normally distributed. A standard strategy to accomplish the normality assumption is data transformation (Mukherjee, White and Wuyts, 1998). However, this strategy is not always able to produce normally distributed data. Second, homoscedasticity ensures that the conditional variance is invariant with the explanatory variables. If the normality and homoscedasticity assumptions are violated, then OLS is a less powerful method for estimating the relationship for the whole sample. A standard strategy to meet the homoscedasticity assumption is to estimate a Generalized Least Square (GLS) regression, in which the data are weighted by their variances. Third, another feature of much social science research data is the presence of outliers, with observations that deviate to an exceptional extent from the majority pattern. How to treat outliers in OLS regression is not straightforward: the outliers can either be removed from the sample, or they can be kept in the sample. The decision as to what strategy to apply depends upon an assessment of the nature of the outliers (are they 'real', or might they be the result of some error?) and the robustness of the regression results for whether or not they are removed from the sample (Cohen, Cohen, West and Aiken, 2003).

Quantile Regression estimates the *conditional quantiles of a response variable* in a linear model, providing a complete view of the possible causal relationships between a response variable and explanatory variables (Koenker and Hallock, 2001; Koenker and Bassett, 1978). Hence, compared to OLS regression, which only estimates the *conditional mean of a response variable*, Quantile Regression provides a more comprehensive picture of the set of relationships between a response variable and explanatory variables, depending upon the value of the response variable. In other words, an OLS regression only estimates the mean of the response variable for each value of the explanatory variables, whereas Quantile Regression estimates all quantile values of the response variable, given the value of explanatory variables. How Quantile Regression works, vis-à-vis OLS, is illustrated in Figures 1.a, 1.b and 1.c, with each figure representing one particular case. We make these three panels to clearly distinguish between three cases: with all OLS assumptions satisfied (Figure 1.a), with the homoscedasticity assumption violated (Figure 1.b), and with a skewed distribution and outliers (Figure 1.c). We present three-dimensional figures, in which y is a response variable, x denotes an explanatory variable, and the third axis gives density.

[Insert Figures 1.a to c about here]

Figure 1.a gives the benchmark case in which the data perfectly fulfil the normality, homoscedasticity and no-outlier assumptions. In this case, estimation of the conditional mean of the response variable is representative for the relationship between the response variable and explanatory variables. If we perform Quantile Regression, all the coefficients that are estimated for each and every quantile are exactly equal to the coefficient produced by OLS regression for the mean. We can see that then, for a given x_1, the value of y_1 could be y_1^a, y_1^b, y_1^c or any other

value of y along the dashed line across y_1^a, y_1^b and y_1^c. Similarly for a given x_2, the value of y could be y_2^a, y_2^b, y_2^c or any other value of y along the dashed line across y_2^a, y_2^b and y_2^c. Applying similar logic, we could draw the value of y for a given x_3. In Figure 1.a, the mean regression line is " $\hat{y}$ for OLS", in which the line links average values of y for given values of x. Clearly, this regression line is representative for the model that specifies the relationship between y and x if the assumptions to perform OLS regression are all fulfilled: normal distribution, equal variance (homoscedasticity), and absence of outliers. Moreover, if we perform Quantile Regression to estimate values of a conditional quantile of y, the slope of the quantile regression line should not be different from the OLS regression line. For example, assume that the value of y at quantile 0.10 given x_1 is y_1^a, given x_2 is y_2^a and given x^3 is y_3^a. Then, the quantile 0.10 regression line is " $\hat{y}$ for Q0.10". If this regression line runs parallel with the " $\hat{y}$ for OLS", then the regression coefficients associated with both lines are equal. Similarly, estimating the quantile 0.90 regression line (" $\hat{y}$ for Q0.90") produces the regression line that runs parallel with the " $\hat{y}$ for OLS" and " $\hat{y}$ for Q0.10" lines. And so on and so forth.

However, if the assumptions of the OLS regression are violated, then the mean regression line will *not* be representative, and hence this line will *not* adequately demonstrate the relationship between the response and explanatory variables. The case with a violation of the homoscedasticity assumption is illustrated in Figure 1.b, and the case with skewed data is illustrated in Figure 1.c. In Figure 1.b, we can see that the conditional variance is not equal at all values of x. In this case, the OLS regression line is not adequately representing the relationship between the response and the explanatory variables for the whole sample. For example, at the quantiles 0.10 and 0.90, the slopes of both regression lines (which are at " $\hat{y}$ for Q0.10" and " $\hat{y}$ for Q0.90", respectively) are different from " $\hat{y}$ for OLS". Therefore, the coefficient estimates produced by OLS regression when the conditional variance is unequal cannot adequately capture the shape the relationship between the response and the explanatory variables for the whole sample.

Figure 1.c illustrates the case in which the normality and no-outlier assumptions are violated. We can now observe that for a given x_3 the conditional distribution of y is positively skewed and heavily tailed. In this case, the regression line that results from applying the OLS method is not representative for the relationship between the response and the explanatory variables. If data are skewed, than the mean value does not coincide with the median. In this type of data, the median is more representative for a central tendency than the mean. If data reveal extreme values or outliers, then the median is a better measure of a central tendency, too, since the median is not sensitive to extreme values. Therefore, Hao and Naiman (2007) suggest that the median regression model can be applied to represent the relationship between the central location of the response variables and explanatory variable(s) when the data distribution is skewed and outliers are present. Since the median is only one case of the quantile distribution of the response variable, we could expand this estimation to other quantiles of the distribution.

Then, we could estimate all quantiles in the distribution by using what is referred to as Quantile Regression. By running this regression, we can figure out what the effect is of an explanatory variable x on a response variable y in a way that is more comprehensive than OLS, which only estimates the conditional mean of y given x. This is essential to our argument. If OLS is applied to data for which the standard assumptions are violated, the regression results will wrongly suggest a uniform x-y relationship, suppressing the actual variety of x-y linkages in the data conditional on where in the distribution y is located. With Quantile regression, different regression lines are estimated for different quantiles. In so doing, the variety of x-y relations will be revealed, provided there are any in the data, with a method that is relatively robust for violation of the three standard assumptions of OLS – normality, homoscedasticity and absence of outliers.

An additional insight that can be derived from interpreting the coefficients produced by Quantile regression, compared to OLS regression, is that we can reveal the relationship between independent and dependent variables at different conditional quantiles – i.e., at different quantiles of the response variable. In our setting, the low quantile regression line represents the relationship between our independent board variables and the dependent performance variable for low-performing enterprises. In contrast, the high quantile regression line represents the relationship between our independent board variables and the dependent performance variable for high-performing enterprises. In the case of an OLS regression, the regression line represents only the conditional mean of the relationship between independent (board) and dependent (performance) variables.

Formally, following Koenker and Basset (1978), a conditional quantile function can be expressed as follows:

$$Q_\theta(y_i \mid x) = \alpha(\theta) + x_i{}'\beta(\theta) \text{ with } \theta \in (0,1), \qquad [1]$$

where y_i is the response variable of observation i, x_i is vector of covariates representing individual observation i, θ represents the θ^{th} quantile, and subscript *i = 1, 2... n* reflects an index for individual observations. $Q_\theta(y_i \mid x)$ denotes the θ^{th} conditional quantile of y_i given x_i. By way of comparison, recall that the OLS regression function is expressed as $E(y \mid x) = \mu_{y|x} = \alpha + x_i\beta$, which is the classical linear function that estimates the conditional mean $\mu_{y|x}$, namely the average value of *y* for the given value of *x*.

The optimization problem of the conditional quantile function is

$$\min_{\beta \in \Re^K} \left[\sum_{i \in \{i: y_i \geq x'_i \beta^{(\theta)}\}} \theta \,|\, y_i - x_i' \beta^{(\theta)} \,|+ \sum_{i \in \{i: y_i < x'_i \beta^{(\theta)}\}} (1-\theta) \,|\, y_i - x_i' \beta^{(\theta)} \,| \right] \quad [2]$$

The optimization problem of this function is to search for the θ^{th} quantile regression estimators $\left(\beta^{(\vartheta)}\right)$ that minimize the absolute value of a weighted sum of the residuals between observed values (y_i) and its fitted values $\left(x_i^{'}\beta\right)$. We assign a weight of θ to the points lying below the quantile regression line (the first term in Equation [2]), and a weight of (1-θ) to the points located above the quantile regression line (the second term in Equation [2]). Note that the estimation of quantile regression coefficients is based on the weighted sum of the residuals for the whole sample, and not just on the portion of the sample at that quantile. Therefore, we never lose degrees of freedom, which is especially important when number of observations in the sample is not very large. The optimization problem of the quantile regression function can be solved by linear programming methods (see Hao and Naiman, 2007, for algorithmic details), since the problem is based on order statistics without having an explicit form (Buchinski, 1994). The solution method is different from the Ordinary (mean) Least Square regression function, which can be solved by taking first-order derivatives to search for optimal regression coefficients that minimize the sum of the squared residuals.

4. Data

Our dependent or response variable is firm performance, measured in terms of the average value of return on assets (<u>ROA</u>) in 2001-2002, being defined as Earning before Interest and Tax (EBIT) divided by total assets (book value). Our independent or explanatory variables are two heavily studied corporate governance mechanisms: (a) the proportion of independent directors (<u>Independent Directors</u>) and Chief Executive Officer (CEO) duality (<u>CEO Duality</u> – i.e., implying that the CEO of the firm serves as the chairman of the board as well). We coded CEO duality as 1, and non-duality as 0. Additionally, we added control variables to the model, known from the literature to affect firm performance: assets (book value in million US$), board size, fixed assets to sales ratio (book value), debt to equity ratio (book value), growth of sales in 1997-2002, and year of first stock exchange listing (up to 2002). Industry dummies are included to correct for industry effects. Our data are taken from the survey conducted by Nam and Nam (2004). We also add some data from annual reports of companies listed on four stock exchanges, namely those of Indonesia, South Korea, Malaysia and Thailand, in case missing data needed to be collected. The sample consists of 66 Indonesian, 111 Korean, 75 Malaysian and 61 Thai firms.

Applying Quantile Regression rather than OLS only makes sense if the data violate the assumptions of OLS regression. Data are normally distributed if the value of skewness is zero and kurtosis is lower than 3. If skewness is zero, the distribution of the data is symmetric. If kurtosis is lower than 3, the tails of the data are thin (Mukherjee, White and Wuyts, 1998). Table 3 provides the relevant descriptive statistics for our variables.

[Insert Table 3 about here]

The data are transformed into natural logarithms and standardized such that the mean value would be zero and standard deviation would be one if the variable at hand is normally distributed. We can see that the skewness value for all variables is not close to zero, indicating that the variables are not symmetrically distributed. Additionally, the kurtosis value is above 3 for four variables – i.e., ROA, proportion of independent directors, fixed assets per sales and growth of sales. This signals observations with extreme values. Moreover, the mean is different from the median for three variables: CEO duality, assets and debt to equity ratio. This implies that the distribution of the data is not bell-shaped. The Jarque-Bera normality test for each variable indicates that only for the board size variable we cannot reject the null hypothesis that the data are normally distributed [$\chi^2(2) = 4.48$ and $p < 0.10$)]. For the other variables, we reject the null hypothesis that the data are normally distributed at the 1% level of confidence with two degrees of freedom. In all, these data diagnostics suggest that Quantile Regression may be more appropriate than OLS regression to figure out if and how the relationship between corporate governance and firm performance might differ across quantiles.

5. Evidence

Table 4 presents Quantile Regresion results for the 0.1, 0.25, 0.50, 0.75 and 0.90 quantiles. By way of comparison, the second column reports the OLS regression estimates. We use the "qreg" command in STATA's (version 9.2) statistical software. The results show that in the OLS regression none of corporate governance variables is significant. However, in the Quantile Regression, we find that the proportion of independent directors significantly affects ROA at quantile 0.50 (0.13, with $p < 0.05$), and that CEO duality significantly affects ROA at quantile 0.5 (0.006, with $p < 0.10$) and quantile 0.75 (0.012, with $p < 0.05$). The OLS results indicate that estimating only the conditional mean of response variable is inappropriate since the data fail to meet the assumptions needed to perform an OLS regression analysis. Checking for normality of the residuals, using the Shapiro-Wilk W test, shows that we must reject the null hypothesis that the residuals are normally distributed ($W = 0.76$ and $p < 0.01$). Checking for homoscedasticity of the residuals, using the Breusch-Pagan test, indicates that we have to reject the null hypothesis that the variance of the residuals is homogeneous [$\chi^2(1) = 62.42$ and $p < 0.01$]. The different results for OLS vis-à-vis Quantile Regression are therefore not surprising. In this case, estimating the effect of corporate governance variables on firm performance at different points of the firm performance conditional distribution using Quantile Regression is more functional since each quantile may be associated with different effects.

[Insert Table 4, and Figures 2.a and b about here]

The Quantile Regression results reveal, indeed, that the effects of corporate governance variables differ across the quantiles in the conditional distribution of firm performance. The effects in different quantiles can be seen in Figure 2.a and 2.b for the proportion of independent directors and CEO duality, respectively. These figures are produced in STATA using the “grqreg” command after running the “qreg” command. We are particularly interested in how the effect of a corporate governance mechanism varies with the quantiles. Note that we only report the findings for our corporate governance variables, for the sake of parsimony and given our theoretical focus, and not for the control variables. We plot the coefficients of corporate governance variables along the vertical axis and the quantiles along the horizontal axis. The line in the middle of the shaded area reflects the coefficient estimates of the Quantile Regression in different quantiles. The dashed line in each figure gives the standard OLS estimate of the conditional mean effect. The shaded grey area depicts a 90 per cent pointwise confidence band for the Quantile Regression estimates.

Figure 2.a shows that the proportion of independent directors has the largest effect around the 0.5 quantile, being smaller in all quantiles above and below 0.5. Almost all coefficients of the Quantile Regression are lower than the estimate from the OLS regression, except for quantile 0.5. These results support agency theory, and hence H1, arguing that particularly independent directors can effectively monitor managers. However, the effect is not significant in the quantile lower than 0.3 and in the quantile higher than 0.7, which is indicated by very broad band of the interval of confidence. These results imply that the proportion of independent directors is an effective governance mechanism mediocre performing firms, but not for under-performing and

top-performing firms. So, the Quantile Regression analysis reveals that the effect of proportion of independent directors is different across quantiles. In a standard OLS regression, this cannot be revealed as only a single estimate is produced, which is conditional on the mean.

Figure 2.b shows that CEO duality is statistically significant in the range from quantiles 0.3 to 0.7. This finding supports stewardship theory's logic, and hence H2Alt, that having the CEO and the chairman of the board position in one hand is important to build effective and strong leadership. Interestingly, we can observe that the effect of CEO duality on firm performance is larger in higher quantiles. This means that the effect of CEO duality on firm performance is larger for better performing firms. Additionally, the results show that CEO duality is not significant in low quantiles (< 0.3) and in high quantiles (> 0.7). This implies that CEO duality as a corporate governance mechanism is not functioning well for under-performing and top-performing firms. Again, these findings show that the relationship between CEO duality and firm performance is different across quantiles, which is something that cannot be captured by applying the classical linear (OLS) regression.

6. Conclusion

Our application of Quantile Regression in the context of the relationship between corporate governance and firm performance revealed that the pair of prominent corporate governance mechanisms focused upon here – proportion of independent directors and CEO duality – has an effect on firm performance only for firms with average performance, and not for firms performing below or above par. The insignificance of both corporate governance practices for the top-performing firms may be caused by the fact that the adoption of these practices by excellent firms operates as a signal that they behave well, which is in line with the expectations of the outside world anyway. The reason why our pair of corporate governance practices is not helpful to enforce performance of under-performing firms may be that such firms are so engaged by more serious issues that the marginal contribution of corporate governance is close to zero. It is this subtle type of conditional linkages that Quantile Regression can help to reveal, so uncovering hidden relationships. In so doing, this method can explain partly inconsistent findings reported in the extant literature, revealing that the relationship between corporate governance mechanisms and firm performance depends on the firm's performing rank.

As Quantile Regression is an advanced method new to the corporate governance literature, we described how Quantile Regression works. The advantage of this regression method, compared to the classical OLS alternative, is that we can now produce separate estimates for different conditional quantiles of response variables. Moreover, Quantile Regression can deal with violations of the standard OLS assumptions of normality, homoscedasticity and absence of outliers. The key advantage of Quantile Regression vis-à-vis OLS and its offsprings is that a series of quantile-specific estimates are produced. In so doing, Quantile Regression may reveal different relationships across the quantiles, which offers a better way to understand mixed predictions from the literature. Contradictory predictions and mixed evidence are omnipresent in the organization sciences, generally, and corporate governance, particularly. Quantile Regression offers a novel tool to explore such differences. Of course, Quantile Regression cannot tell the whole story. What Quantile Regression does is to make the estimate conditional on the value of the response variable. Other reasons for contradictory or mixed findings, such as contingencies in the realm of explanatory variables, have to be explored with other tools, such as interaction terms.

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Table 1. Summary of the Studies on Board Independence

Author(s)	Independent Variable	Dependent Variable	Data	Results	Methods
Baysinger and Butler (1985)	Prop. of Independent Directors	Relative Return on Equity	266 major US corps. *Forbes*	Significantly positive	Simultaneous Equation Regression
Chaganti *et al.* (1985)	Prop. of Outside Directors	Firm failure	21 pairs of retailing firms in the US	Not significant	ANOVA
Kesner *et al.* (1986)	Prop. of Outside Directors	Illegal activities	384 firms of *Fortune 500*	Not significant	ANOVA and OLS regression
Kesner (1987)	Prop. of Inside Directors	Profit margin	205 firms of *Fortune 500*	Significantly positive	Correlation Analysis
		Return on Equity		Not significant	
		Return on Assets		Significantly positive	
		Earning per Share		Not significant	
		Stock Market Performance		Significantly negative	
		Total return to Investors		Not significant	
Schellenger *et al.*(1989)	Prop. of Outside Directors	Return on Assets	526 random firms from *Compustat* Database	Significantly positive	Correlation Analysis
		Return on Equity		Not significant	
		Return on Investment		Not significant	
Rosenstein and Wyatt (1990)	Prop. of Financial Outside Directors	Abnornal market return	NYSE and AMEX Corporations	Significantly positive	Weighted Least Square
	Prop. of Corporate Outside Directors			Not significant	
	Prop. of Neutral Outside Directors			Significantly positive	
Pearce II and Zahra (1992)	Prop. of Outside Directors	Return on Assets	450 firms from *Fortune 500*	Significantly positive	MANOVA
		Return on Equity		Significantly positive	
		Earning per Share		Significantly positive	
		Net Profit Margin		Not significant	
Daily and Dalton (1992)	Prop. of Outside Directors	Return on Assets	100 US firms listed in *Inc.* Magazine	Not significant	ANOVA and MANOVA
		Return on Equity		Not significant	
		Price Earning Ratio		Outside significantly higher	
Daily and Dalton (1993)	Prop. of Outside Directors	ROA	186 small firms listed in the US	Significantly positive	MANOVA
		ROE			
		PER			
Ezzamel and Watson (1993)	Prop. of Independent Directors	Average Profit to Capital Ratio	184 UK companies from *Exstat* database and *Hambro* Company Guide	Not significant	Linear regression
		Change in Profit to Capital Ratio		Significantly positive	
Agrawal and Knoeber (1996)	Prop. of Outside Directors	Tobin's Q	400 US large firms	Significantly negative	OLS and 2SLS regression
Yermack (1996)	Prop. of Outside Directors	Tobin's Q	452 large US industrial corporations	Significantly negative	OLS regression with fixed effect
Klein (1998)	Prop. of Outside Directors	ROA	641 firms in listed *S&P 500*	Not significant	OLS regression
		Productivity		Significantly negative	
		Market return		Not significant	
	Prop. of Inside Directors on Finance	Productivity		Significantly positive	
	Prop. of Inside Directors on Investment	ROA		Significantly positive	

	Prop. of Inside Directors on Audit Committee	ROA		Not significant	
		Productivity		Not significant	
		Market return		Not significant	
	Prop. of Inside Directors on Compensation Committee	Productivity		Significantly negative	
Bhagat and Black (2002)	Board Independent (Prop. of Indep minus Prop. of Inside)	Tobin's Q	934 US large corporations	Significantly negative	OLS and 3SLS regression
		Operating Income to Assets Ratio		Significantly negative	
		Sales to Assets Ratio		Not significant	
		Stock Price Return		Not significant	
		Assets Growth		Not significant	
		Operating Income Growth		Not significant	
		Sales Growth		Not significant	
Kiel and Nicholson (2003)	Prop. of Outside Directors	Tobin's Q	348 Australian listed corporations	Significantly negative	Linear regression and correlation analysis
		ROA		Not significant	
Ghosh (2006)	Prop. of Non-Exec. Directors	ROA	127 listed manufacturing firms in India	Not significant	Linear regression
		Adjusted Tobin's Q		Not significant	
		Average value of ROA, ROE and ROS		Not significant	
Cheung *et al.* (2006)	Prop. of Indep Non executive Dir	Market-Adjusted CAR	Listed firms in Hong Kong	Not significant	OLS regression
Cho and Kim (2007)	Outside Directors Participation Rate	Return on Assets		Significantly positive	Linear regression
Al Farooque *et al.* (2007)	Prop. of Non-Executive Directors	Market to Book Value Equity	723 firms in Bangladesh	Not significant	OLS and 2SLS regression
Cornett (2008)	Prop. of Outside Directors	Adjusted EBIT/Assets	100 firms of *S&P Index*	Significantly negative	Pooled and panel data regression
Coles *et al.* (2008)	Prop. of Inside Directors	Tobin's Q	*Execucomp* database	Significantly negative	3SLS regression

Table 2. Summary of the Studies on CEO Duality

Author(s)	Independent Variable	Dependent Variable	Data	Results	Methods
Chaganti *et al.* (1985)	CEO Duality	Firm failure	21 pairs of retailing firms in the US	Not significant	ANOVA
Kesner *et al.* (1986)	CEO Duality	Illegal activities	384 firms of *Fortune 500*	Not significant	ANOVA
Rechner and Dalton (1991)	CEO Duality	Return on Investment	141 companies of *Fortune 500*	Duality significantly lower	ANOVA and MANOVA
		Return on Equity		Duality significantly lower	
		Profit Margin		Duality significantly lower	
Donaldson and Davis (1991)	CEO Duality	Return on Equity	337 US corporations	Duality significantly higher	ANOVA
Daily and Dalton (1992)	CEO Duality	Return on Assets	100 US firms listed in *Inc.* Magazine	Not significant	ANOVA and MANOVA
		Return on Equity		Not significant	
		Price Earning Ratio		Not significant	
Pi and Timme (1993)	CEO Duality	Cost efficiency	112 publicly traded US commercial banks	Significantly negative	OLS regression
		Return on Assets		Not significant	
Daily and Dalton (1993)	CEO Duality	ROA	186 small listed corporations in the US	Not significant	MANOVA
		ROE		Not significant	
		PER		Not significant	
Baliga *et al.* (1996)	CEO Non-Duality	Market value of the firm	172 firms of *Fortune 500*	Not significant	OLS regression
Kiel and Nicholson (2003)	CEO Duality	Tobin's Q	348 Australian listed corporations	Significantly negative	Linear regression
		ROA		Not significant	
Cheung *et al.* (2006)	CEO Duality	Market-Adjusted CAR	Listed firms in Hong Kong	Not significant	OLS regression
Al Farooque *et al.* (2007)	CEO Duality	Market to Book Value Equity	723 firms in Bangladesh	Not significant	OLS and 2SLS regression
Elsayed (2007)	CEO Duality	Return on Assets		Not significant	Least Absolute Value regression
		Tobin's Q		Not significant	
Cornett (2008)	Lagged CEO Duality	Adjusted EBIT/Assets	100 firms of S&P Index	Significantly positive	Panel data regression

Table 3. Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
ROA	0.000	0.002	0.058	-0.555	0.381	-2.376	36.893
Proportion of Independent Directors	0.000	-0.002	0.017	-0.030	0.066	0.486	4.390
CEO Duality (Yes = 1; No = 0)	0.000	-0.392	0.488	-0.392	0.608	0.444	1.203
Board Size	0.000	0.020	0.416	-1.367	1.076	-0.293	2.988
Assets	0.000	-1.069	4.103	-7.206	9.276	0.307	1.774
Fixed Assets per Sales	0.000	-0.030	1.285	-6.736	5.081	-0.463	7.558
Debt to Equity Ratio	0.000	-0.847	3.921	-6.832	7.672	0.223	1.729
Growth Sales	0.000	0.016	1.401	-9.832	6.584	-1.761	23.839
Year Listed	0.000	0.095	0.826	-2.390	1.460	-1.225	4.516

Table 4. OLS and Quantile Regression Results

Independent Variable ROA	OLS			Q0.1			Q0.25			Q0.5 , Median			Q0.75			Q0.90		
	Coef.	SE	T	Coef.	SE	t	Coef.	SE	t	Coef.	SE	t	Coef.	SE	t	Coef.	SE	t
Corporate Governance Variables																		
Independent Directors	.267	.273	.98	-.243	.738	-.33	-.046	.226	-.20	.283**	.130	2.18	.078	.350	.22	-.191	.709	-.27
CEO Duality (Yes = 1; No = 0)	.015	.011	1.32	.006	.032	.18	.009	.010	.93	.010*	.006	1.89	.028**	.012	2.25	.029	.019	1.50
Control Variables																		
Board Size	.023**	.011	2.12	.040*	.022	1.79	.013	.009	1.45	.010	.005	1.84	.011	.013	.84	.012	.027	.46
Assets	.012***	.004	2.89	.014	.019	.74	.010**	.004	2.48	.006***	.002	2.72	.005	.004	1.23	.001	.007	.20
Fixed Assets per Sales	.007**	.003	2.06	.006	.007	.80	.003	.003	.99	.001	.002	.93	.005	.005	1.12	.002	.013	.13
Debt to Equity Ratio	-.015***	.004	-4.07	-.018	.015	-1.18	-.011***	.003	-3.46	-.007***	.002	-4.06	-.007**	.004	-2.05	-.005	.007	-.74
Growth Sales	.005**	.002	1.99	.009*	.005	1.73	.004*	.002	1.94	.002*	.001	1.86	.001	.003	.28	-.002	.008	-.23
Year Listed	.002	.004	.60	.001	.012	.09	.001	.003	.28	-.001	.002	-.51	-.001	.005	-.16	-.006	.009	-.65
South Korea Dummy	.013	.026	.50	.053	.083	.64	.015	.023	.68	.007	.012	.56	-.016	.029	-.54	-.005	.050	-.10
Malaysia Dummy	-.001	.015	-.08	.003	.033	.09	-.001	.012	-.10	.004	.007	.51	.000	.019	.00	.013	.040	.31
Thailand Dummy	-.015	.016	-.94	-.009	.045	-.21	.003	.014	.24	.000	.008	-.01	-.022	.019	-1.13	-.014	.048	-.30
Industrial Dummy	Yes			Yes			Yes			Yes			Yes			Yes		
Constant	-.005	.015	-.31	-.072	.047	-1.55	-.037	.014	-2.74	-.006	.007	-.82	.038	.017	2.18	.053	.033	1.58
Preudo R^2 , R^2 for OLS	.139			.160			.0826			.079			.0684			.112		

* *p* < .1; ** *p* < .05; and *** *p* < .01.

Figure 1.a Normal distribution and homoscedasticity case

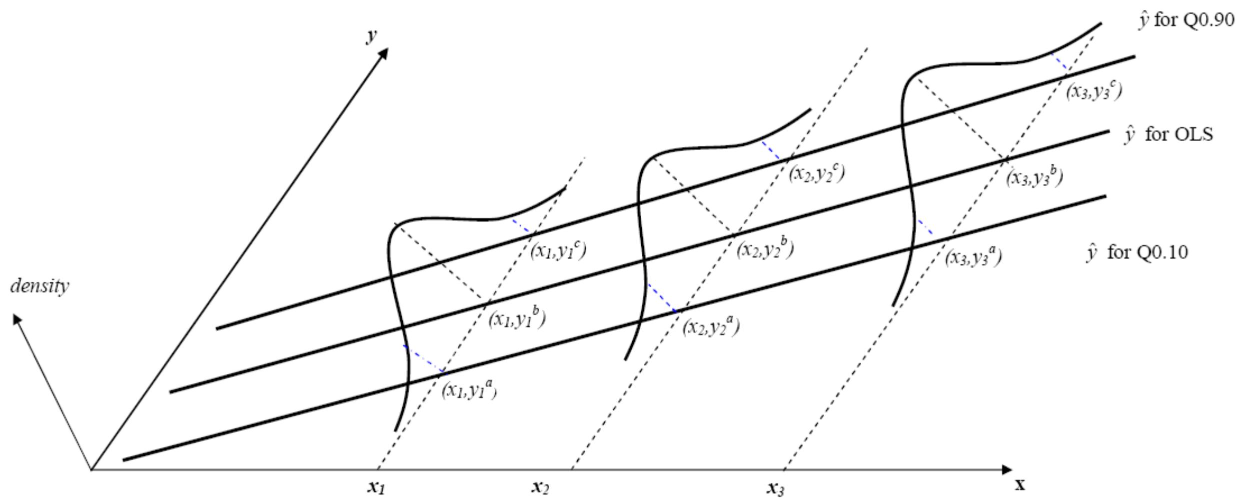

Figure 1.b Normal distribution but heteroscedasticity case

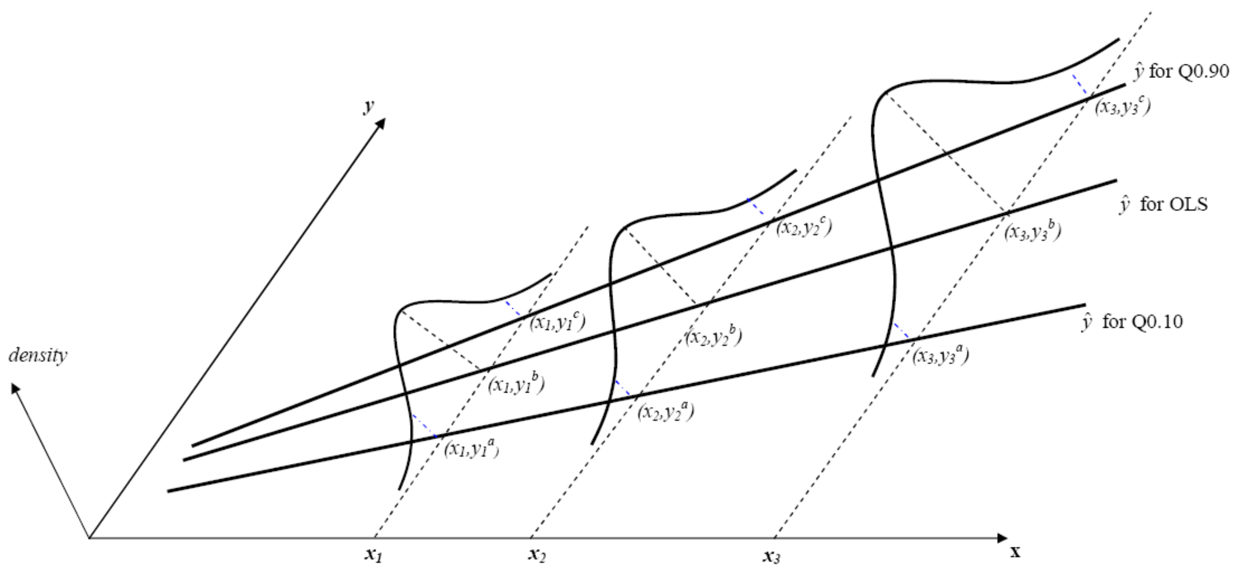

Figure 1.c Skewed distribution and outlier case

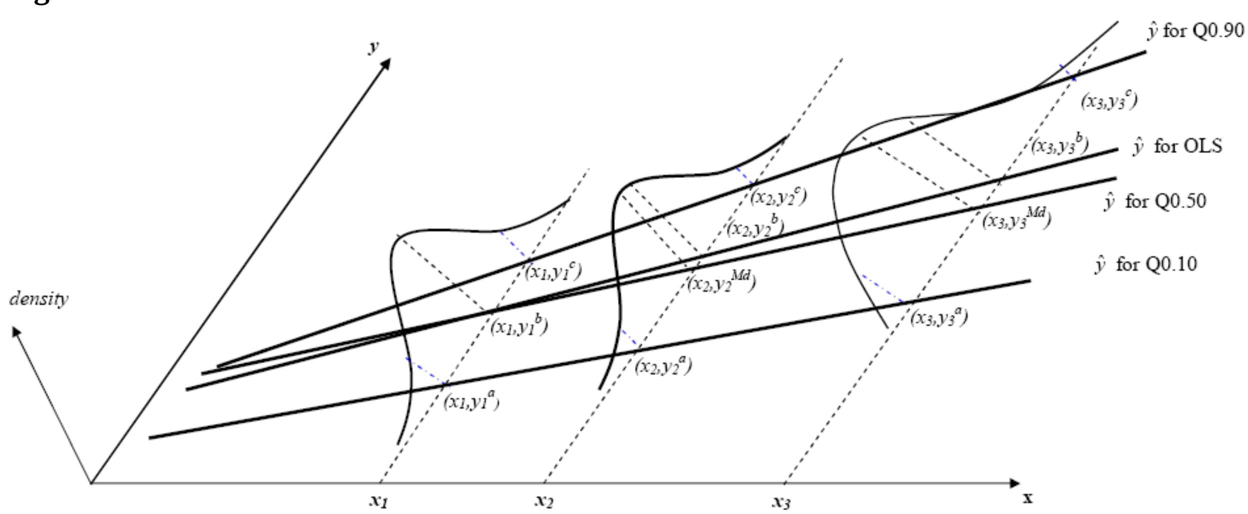

Figure 2: Plot of the estimates for independent directors , a and CEO duality , b