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Endogeneity and the Dynamics of Corporate Governance ⋆

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Abstract

Research in corporate finance is complicated by the endogenous relation between the control forces operating on a corporation and its financial decisions. In this paper we adapt a dynamic panel GMM estimator to deal with endogeneity in corporate finance research. The estimator incorporates the dynamic nature of corporate finance relationships to provide valid and powerful instruments that control for unobserved heterogeneity and simultaneity. The estimator is straightforward to implement and is more theoretically and practically appealing than many recent attempts to deal with endogeneity. Further, it may have significant advantages over commonly used fixed-effects estimators. We then demonstrate the estimator empirically by re-examining the relation between board structure and performance in a panel of more than 6,000 firms between 1991 and 2003. We find that when we control for past performance, simultaneity and unobservable heterogeneity, there is no causal relation between board structure and current firm performance. We illustrate why existing research that has found a causal relation is likely to be biased. We discuss situations where using this estimator will provide the greatest benefits.

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1 Introduction

It is well known that research in corporate finance is complicated by the endogenous relation that exists between the control forces operating on a corporation and its financial decisions. Jensen (1993) broadly classifies these control forces (i.e., governance) as capital markets, the regulatory system, product and factor markets and internal governance.[1] In much of the extant corporate finance research, researchers attempt to either explain the causes or examine the effects of a corporate finance decision as related to one or more of these control forces. Thus, empirical corporate finance research often involves determining the causal effect, if any, of a firm characteristic (X) on some measure of firm profits or value (Y). This is usually done using the inference from a regression of Y on X and typically includes many control variables (Z). The question is often framed as follows: holding Z constant, does X have an economically and statistically significant causal effect on Y?

To date, most empirical research in corporate finance has explicitly recognized at least two sources of endogeneity that may bias estimates of how X affects Y: *unobservable heterogeneity* (which arises if there are unobservable factors that affect both the dependent and explanatory variables) and *simultaneity* (which arises if the independent variables are a function of the dependent variable or expected values of the dependent variable). However, we argue that empirical research has generally overlooked an important source of endogeneity that arises because of the fact that the relations among a firm's observable characteristics are likely to be dynamic. That is, a firm's current actions will affect its control environment and future performance, which will in turn affect its future actions. For example, in the context of governance, current firm performance will affect future governance choices and these may, in turn, affect future firm performance. We define this relationship as *dynamic endogeneity* and refer to it as such throughout the paper. As in Himmelberg, Hubbard, and Palia (1999), we do not intend to minimize or ignore the importance of agency conflicts or suggest that governance is irrelevant; rather we argue that the cross-sectional variation in observed governance structures is driven by *both* unobservable heterogeneity *and* the firm's history. As such, any attempt to explain the determinants of governance or its effect on performance that

[1] Throughout the paper, we use the term governance to mean all control forces, of which internal or corporate governance is a subset.

does not recognize these sources of endogeneity may be biased.

In this paper, we specifically examine how dynamic endogeneity impacts research efforts to measure the causal relation between governance (broadly defined) and firm performance. First, we show, theoretically and numerically, that ignoring dynamic endogeneity can lead to biased inference about the relation between governance and firm performance. For example, the literature's focus on unobservable heterogeneity as the major source of endogeneity in prior research has led to widespread use of panel data. However, traditional fixed-effects (or "within") estimates that eliminate unobservable heterogeneity are only consistent under the assumption that firm characteristics or corporate structures are strictly exogenous. That is, that they are random draws through time and are unrelated to the firm's history. This is a strong assumption that is often at odds with the theory and is unlikely to hold in practice. So, while OLS estimation may be biased because it ignores unobservable heterogeneity, fixed-effects estimation may be biased since it ignores dynamic endogeneity.

Next, we show how to use a dynamic panel GMM estimator to appropriately estimate the relation between governance and firm performance. This methodology not only eliminates any bias that may arise from ignoring dynamic endogeneity, but also provides theoretically based and powerful instruments that account for simultaneity while eliminating any unobservable heterogeneity. Dynamic panel estimation is most useful in situations where some unobservable factor affects both the dependent variable and the explanatory variables, and some explanatory variables are *strongly* related to past values of the dependent variable. This is likely to be the case in regressions of performance on governance since performance has a strong, immediate and persistent effect on governance. Dynamic endogeneity is less of a concern in regressions relating governance to firm characteristics because there is a weaker relationship between the explanatory variables and past realizations of the dependent variable.

Finally, to illustrate this methodology empirically, we apply it to two important and extensively studied aspect of internal governance – (i) the relation between board structure and firm performance and (ii) the determinants of board structure. These applications illustrate the benefits of the methodology and provide important new empirical results on the governance/performance

relation. In recent surveys of the board literature, Hermalin and Weisbach (2003) and Adams, Hermalin, and Weisbach (2009) suggest that inference in board research is complicated by the fact that current board actions can affect firm performance as well as the future make-up of boards, and vice-versa. Most empirical research on boards inadvertently misses this dynamic aspect of the board/performance relation. Our analysis aims to fill this gap.

In our first empirical application, we find that when we control for past performance, simultaneity and unobservable heterogeneity, there is no causal relation between board structure and current firm performance. This is in sharp contrast to the findings of some earlier studies. We show how the biases inherent in specifications used would lead to the correlations observed in some existing research. We also show that our results are not driven by lack of power or weak instruments. We are able to reject both the null of weak instruments and the null that our instruments are not exogenous.

In our second application, we examine the effects of firm characteristics on board structure, where these characteristics proxy for different aspects of the firm's operating and contracting environment. We find, even after controlling for unobservable heterogeneity and dynamic endogeneity, that board structure is closely associated with firm size, growth opportunities, firm risk, age, leverage and past performance. These results are similar to those obtained in recent studies by Boone, Field, Karpoff, and Raheja (2007) and Linck, Netter, and Yang (2008). However, this application also demonstrates the importance of controlling for both dynamic endogeneity and unobservable heterogeneity. For example, the estimated magnitude of the effect of firm size on board size (independence) from GMM regressions, while still significant, is 66% (58%) smaller than the estimated magnitude of the effect from OLS regressions suggesting that OLS estimates may be biased upwards because of the combination of unobservable heterogeneity and dynamic endogeneity.

In terms of the issues addressed, our paper is similar to that by Coles, Lemmon, and Meschke (2008), who examine the relation between ownership and performance. They show how specifying a structural model of the firm can minimize endogeneity problems that plague empirical corporate finance research. Their conclusions are similar to ours. Both papers find that a measure of governance (ownership in the Coles, Lemmon, and Meschke (2008) paper, board structure in

this paper) and performance are determined endogenously, rather than governance driving performance. However, our approach is fundamentally different from theirs. Under our approach, the researcher needs only the firm's historical performance and characteristics. The researcher does not need to know the exact specification of the unobservable process that generates the endogenous variables.

Our results help reconcile some of the conflicting results in the prior literature and explain how some reported correlations could arise from ignoring one or more aspects of the endogeneity inherent in the board structure/performance relation. For example, we argue that a negative relation between board independence and past firm performance induces a positive bias when measuring the effect of board independence on current firm performance with a static fixed-effects regression. Similarly, we predict and find a negative bias when measuring the effect of board size on firm performance from a fixed-effects regression given the positive relation we observe between board size and past performance. We also show that these issues are important in many areas of empirical corporate finance.[2] However, accounting for historical persistence and dynamic endogeneity is particularly important in corporate governance since most studies in that area seek to determine the effect of governance on performance, an aspect of research that is particularly susceptible to biases that may arise by ignoring historical persistence and dynamic endogeneity.

The fact that we do not find a cross-sectional relation between governance and firm performance does not mean that governance is irrelevant; indeed we view our results as suggesting the opposite. However, our results do suggest than an arbitrary change of board structure in one direction (increasing independence or decreasing size) will not necessarily increase value. For some firms, moving towards a larger or less independent board may be value-maximizing. Our results strongly that the value-maximizing board that will emerge for any particular firm depends on the firm's characteristics, its operating and contractual opportunity set and the firm's historical performance as reflected in its characteristics and opportunity set.

The rest of the paper is organized as follows. In section 2, we discuss related literature and

[2]For example, Lemmon, Roberts, and Zender (2008, p. 1605) argue for the importance of accounting for unobservable heterogeneity and persistence with "dynamic specifications" in estimating the determinants of capital structure. They find that controlling for the dynamics has a material effect on the results.

develop our hypotheses. In section 3, we lay out the theoretical basis for the biases that may arise in commonly used techniques for estimating the relation between governance and performance. We also describe the dynamic panel GMM estimator and perform numerical simulations to illustrate the biases and how to control for them. We describe the data for our empirical application in section 4, and provide an empirical analysis of the relation between board structure and firm performance in section 5. In section 6, we re-examine the determinants of board structure in a dynamic framework. We conclude in section 7. In an appendix, we provide additional details of the GMM estimator, including details for implementing it in STATA.

2 An empirical model for board structure and performance

While endogeneity is pervasive across many aspects of corporate finance, to illustrate the role of dynamic endogeneity, we focus on the relation between board structure and performance. This is an area that has received substantial attention in the literature. As we show in this section, theory and prior empirical work suggests that board structure, like many aspects of a firm's organization or governance, is dynamically endogenous with respect to firm performance.

Table 1 presents a summary of prior studies that have explicitly examined the relation between board structure and firm performance. The results are mixed. For example, most find either a negative relation between board independence and performance (Agrawal and Knoeber (1996); Klein (1998); Bhagat and Black (2002)) or no relation at all (Hermalin and Weisbach (1991); Mehran (1995)). Interestingly, most who argue for a particular level of board independence suggest that more independent boards improve performance through better monitoring of management. Yermack (1996) and Coles, Daniel, and Naveen (2008) do find a positive relation in some specifications. However, more recent evidence suggests that independent boards are not always value enhancing. For example, Adams (2009) finds that financial firms that faced the most severe distress during the 2008/2009 financial crisis, and consequently needed government bailout funds, actually had more independent boards than the financial firms that did not.[3]

[3] Adams (2009) suggests that this may have been due to the lack of experience and industry-specific knowledge of most of the independent directors.

There appears to be more empirical regularity in studies that examine the effect of board size on performance. Most (e.g., Yermack (1996); Eisenberg, Sundgren, and Wells (1998)) report a negative relation between firm performance and board size. The theory is that larger boards are likely to have higher coordination costs, which reduces their ability to effectively monitor management. However, we have not seen a convergence towards uniformly small boards.

2.1 A dynamic model of board structure

In this section, we develop our empirical model of board structure based on the structural models of Hermalin and Weisbach (1998), Raheja (2005) and Harris and Raviv (2008)

Raheja (2005) presents a model in which the optimal board structure is determined by a trade-off between maximizing the incentive for insiders to reveal their private information, minimizing the cost to outsiders to verify projects, and maximizing outsiders' ability to reject inferior projects. Her model suggests that when verification costs are high, optimal boards require more insiders. For example, firms with new technology or firms with unique 'high technology' products often have projects that are difficult for outsiders to verify; thus, her model suggests that such firms may optimally have more insiders on the board. Similarly, Harris and Raviv (2008)'s model suggests that board structure depends on the firm's information and contracting environment. To the extent that observable firm characteristics (e.g., firm size, growth opportunities, age, leverage, etc.) proxy for the firm's information environment, then these firm characteristics should be systematically related to board structure. Boone, Field, Karpoff, and Raheja (2007), Coles, Daniel, and Naveen (2008), Linck, Netter, and Yang (2008), and Lehn, Patro, and Zhao (2008) provide empirical support for this hypothesis.

Hermalin and Weisbach (1998) argue that board independence is the outcome of a bargaining process between the existing CEO and the board. The CEO's bargaining power derives from his perceived ability compared to alternative managers that the firm might be able to hire. They propose that the intensity with which the board monitors the CEO: (i) decreases with its prior estimate of the CEO's ability, (ii) decreases with its precision of its prior estimate and (iii) increases with the precision of its privately acquired signal about the CEO's ability. One implication of this model

is that within any particular period, there will be a *negative* relation between board independence and the ability of the firm's managers. It also suggests that board composition will be related to the firm's past performance – that is, board structure is *dynamically endogenous* with respect to performance. Specifically, board independence will be *negatively* related to the firm's past performance.

Past performance can affect current board structure through another channel. If board structure is determined by firm characteristics and these characteristics are related to past performance, then board structure is related to past performance through the effect of performance on firm characteristics. For example, following arguments presented by Fama and Jensen (1983), Boone, Field, Karpoff, and Raheja (2007) argue that larger firms are more hierarchical, and that the larger firm boards ratify and monitor more decisions of senior managers. It follows that the information requirements of more complex, larger firms will require larger boards. Boone, Field, Karpoff, and Raheja (2007), Coles, Daniel, and Naveen (2008), Linck, Netter, and Yang (2008) and Lehn, Patro, and Zhao (2008), among others, find a positive relation between board size and firm size. Firm size is likely to be *positively* related to firm performance so board size will be *positively* related to past firm performance through the effect of performance on size.

2.2 A dynamic model of firm performance

The discussion in section 2.1 suggests that board structure is a choice variable that arises through a process of bargaining between the various actors in a firm's nexus of contracts, where the bargaining process is influenced by past performance and the actors' beliefs about the costs and benefits of particular board structures. Thus, if board structure is dynamic and firm i (given its performance at time $t-1$ or earlier) chooses a board structure $\mathbf{X}_{it}$ to achieve a level of expected performance $E(y_{it})$ at time t, then the dynamic model for the effect of board structure on performance is:

$$E(y_{it}|y_{it-1}, y_{it-2} \dots y_{it-p}, \mathbf{X}_{it}, \mathbf{Z}_{it}, \eta_i) = \alpha + \sum_s \kappa_s y_{it-s} + \mathbf{b}_i \mathbf{X}_{it} + \gamma_y \mathbf{Z}_{it} + \eta_i \quad s = 1, \dots, p \qquad (1)$$

where $\mathbf{X}$, $\mathbf{Z}$ and y represent board structure, firm characteristics and performance, respectively, η represents an unobserved firm effect and $\mathbf{b}_i$ measures the effect of board structure on firm performance given the firm's historical performance. Including the lagged dependent variables accounts

for the fact that the explanatory variables are themselves related to past performance.

Equation (1) allows for the possibility that the effect of board structure on performance ($\mathbf{b}_i$) may differ across individual firms, which is what is suggested by existing theory and empirical research. A key aspect of equation (1) is that it does not rule out the possibility that firms strategically use board structure to change their performance. However, cross-sectional estimation of (1) will mean estimating the following model:

$$y_{it} = \alpha + \sum_{s} \kappa_s y_{it-s} + \beta \mathbf{X}_{it} + \gamma \mathbf{Z}_{it} + \eta_i + \epsilon_{it} \quad s = 1, \ldots, p \tag{2}$$

where ϵ_{it} is a random error term and β is the average effect of board structure on performance, i.e., $\beta = E(\mathbf{b}_i)$. The key economic question here concerns the inference drawn from the estimated $\hat{\beta}$ in equation (2). The model in (1) allows $\mathbf{b}_i$ to differ across firms. It is of course possible that $\mathbf{b}_i < 0$ for some firms and $\mathbf{b}_i > 0$ for other firms. Thus, while board structure may be important in determining firm performance, if board structure is completely endogenously determined, then $\hat{\beta} = E(\mathbf{b}_i) = 0$.

Another key aspect of equation (1) is that if board structure is a choice variable then it must be based on some expectations of performance. However, the model does not require that we assume that expected performance, $E(y_{it})$, is the one that maximizes firm value. Some firms may overestimate the effect of increasing (or decreasing) board size, while others may underestimate it. Agency and transaction costs may also lead $E(y_{it})$ to be less than value-maximizing. However, once the bargaining has occurred, the board has been chosen and associated expectations have been set, then any innovations to performance would be genuine shocks to the actors in the firm's nexus of contracts with respect to the information the firm used to choose its board structure.

This assumption means that if we estimate estimate equation (2), current shocks are independent of historical realizations of performance or board structure. This is not a stringent assumption since it allows current performance to be influenced by past and current realizations of board structure. The assumption leaves open the possibility that firms strategically choose governance to change current or future performance. If the board structure that we observe today is one that trades off the *anticipated* costs and benefits of particular structures, then the *unanticipated* compo-

nent of performance, many years in the future, will not be related to the board structure that is chosen today. This assumption, which can be written in orthogonality form as $E(\epsilon_{it}|y_{it-s}, \mathbf{X}_{it-s}) = 0$, is particulary important because it provides a theoretical motivation for the choice of instruments that we use to estimate the empirical model of equation (2), as we shall discuss in section 3.

3 Estimating the relation between governance and firm performance

In sections 3.1 and 3.2 we lay out the theoretical basis for the biases that arise when we use OLS or fixed-effects regressions to estimate the relation between governance and firm performance. We then discuss the dynamic panel general method of moments (GMM) estimator, which mitigates these biases. In section 3.3, we use a numerical simulation to illustrate how OLS and fixed-effects estimates are biased due to unobserved heterogeneity and dynamic endogeneity, and how these biases can lead to incorrect inferences. We also use the numerical example to show that the dynamic panel GMM estimator yields powerful and unbiased estimates in the presence of unobserved heterogeneity and dynamic endogeneity.

3.1 Sources of endogeneity in the governance/performance relation

In this section we discuss the souces of econometric endogeneity that may arise with specific reference to the empirical model in equation (2).

3.1.1 Simultaneity

Econometrically, simultaneity exists in equation (2) if $E(\epsilon_{it}|\mathbf{X}_{it}, \mathbf{Z}_{it}) \neq 0$. From an economic perspective, simultaneity can arise in the board structure/performance relation. If, as theory suggests, firms choose their board structure in any period with a view towards achieving a particular level of performance in that period, then while performance may be affected by board structure, the reverse will also be true – board structure will also be affected by performance. In this case, board structure and performance are simultaneously determined and both OLS and fixed-effects estimates of equation (2) will be biased.

One potential solution to the problem of simultaneity is to estimate the effect of board structure

on performance using a system of equations. In one equation, performance is allowed to depend on governance and other controls variables while in other equations, governance is allowed to depend on performance and other control variables. However, estimating this system requires us to identify strictly exogenous instruments – there must be at least one variable in the governance equation that is not also in the performance equation. In practice, identifying and justifying a strictly exogenous instrument is very difficult and sometimes impossible. To further complicate matters, the number of such exogenous instruments increases with the number of equations in the system.

3.1.2 Unobservable heteogeneity, dynamic endogeneity and the bias of fixed-effects estimation

Econometrically, unobservable heterogeneity exists in equation (2) if $E(\eta_i|\mathbf{X}_{it}, \mathbf{Z}_{it}) \neq 0$. Economically, unobservable heterogeneity is a source of endogeneity if there are factors unobservable to the researcher that affect both performance and the explanatory variables. In the board structure/performance context, theory suggests that this is the case. For example, consider the effect of managerial ability which, while generally unobservable, certainly affects performance. However, as we discussed in section (2), Hermalin and Weisbach (1998) suggest that firms with high-ability managers will monitor less and thus, may have less independent boards. Therefore, an OLS regression of performance on board structure that ignores this unobservable heterogeneity may find a *negative* relation between board independence and performance.

A potential solution to unobservable heterogeneity, if panel data is available, is a fixed-effects or “within" estimation. Consider the linear model:

$$y_t = \beta x_t + \eta + \epsilon_t \tag{3}$$

where η represents an unobserved fixed effect. A fixed-effects transformation, which requires time-demeaning all variables yields:

$$\ddot{y}_t = \beta\, \ddot{x}_t + \epsilon_t \tag{4}$$

where $\ddot{x} = x_{it} - \bar{x}_i$ and $\ddot{y} = y_{it} - \bar{y}_i$.

However, what is often not recognized are the conditions under which a fixed-effects regression

would be consistent and unbiased. A fixed-effects regression of the model in equation (2) would be consistent only if current values of the explanatory variables (governance) were completely independent of past realizations of the dependent variable (performance), i.e., if $E(\epsilon_{is}|\mathbf{X}_{it}, \mathbf{Z}_{it}) = 0, \forall s, t$. This means that fixed-effects estimates would be biased if past performance affects current values of governance, i.e., if there is *dynamic endogeneity*. What happens if we inadvertently apply fixed-effects estimation in the presence of dynamic endogeneity? From (Wooldridge (2002)), the limiting value of a fixed-effects estimate of equation (3) is:

$$plim(\hat{\beta}_{FE}) = \beta + \left[\frac{1}{T}\sum_{t-1}^{T} E(\ddot{x}_{it}'\ddot{x}_{it})\right]^{-1}\left[\frac{1}{T}\sum_{t-1}^{T} E(\ddot{x}_{it}'\epsilon_{it})\right] \tag{5}$$

The direction and bias of the fixed-effects estimator will depend on $E(\ddot{x}_{it}'\,\epsilon_{it})$. If we assume that board structure (x) at time t depends on performance (y) at time $t-1$ (or earlier), then:

$$\frac{1}{T}\sum_{t-1}^{T} E(\ddot{x}_{it}'\epsilon_{it}) = -\frac{1}{T}\sum_{t-1}^{T} E(\bar{x}_i'\epsilon_{it}) = -E(\bar{x}_i'\bar{\epsilon}_i) \neq 0 \tag{6}$$

(6) suggests that if the explanatory variable, x is positively (negatively) related to past values of the dependent variable, y, then a fixed-effects estimate of current values of y on current values of x will be negatively (positively) biased. It also suggests that even if there is no causal relation from x to y, a fixed-effects regression could yield a spurious estimate of the effect of x on y.

To further illustrate how a spurious correlation could arise if there is dynamic endogeneity, consider a simple model in which past performance (y) causes changes in governance (x) but x does not cause y. The model can be written as follows:

$$\Delta y_{it} = \epsilon_{it} \tag{7}$$

$$\Delta x_{it} = A(L)\Delta y_{it} + \varepsilon_{it}$$

$$\epsilon_{it}, \varepsilon_{it} \sim i.i.d.,\ N(0,1)$$

where L is the lag operator and $A(L) = a_1L + a_2L^2 + \ldots + a_TL^T$, where all the coefficients have the same sign. Since Δx_{it} is an unambiguously signed linear combination of past changes in y, we

can write each x_{it} as:[4]

$$x_{it} = x_{i0} + C^t(L)\Delta y_{it} + u_{it} \tag{8}$$

where $C^t(L)$ is a time-varying polynomial whose coefficients are all the same sign, x_{i0} is some initial value of x independent of future performance shocks ($E[x_{i0}\epsilon_{it}] = 0$) and where u_{it} is a random error such that $E[\epsilon_{it}u_{js}] = 0$, $\forall i \neq j$ and $t \neq s$.

Substituting (8) into (6) and making use of our assumptions above that x is orthogonal to current or future innovations y, $E[x_{i0}\epsilon_{it}] = E[\epsilon_{it}u_{js}] = 0$ and $\epsilon_{it} \sim i.i.d.,\ N(0,1)$, we get:

$$\begin{aligned} -E(\bar{x}_i'\bar{\epsilon}_i) &= -\frac{1}{T^2}\sum_{t=1}^{T}\left[\sum_{t=1}^{T} x_t \sum_{r=1}^{T}\epsilon_{t-r}\right] = -\frac{1}{T^2}\sum_{t=1}^{T}\left[\sum_{t=1}^{T} C^t(L)\Delta y_t \sum_{r=1}^{T}\epsilon_{t-r}\right] \\ &= -\frac{1}{T^2}\sum_{t=1}^{T}\left[\sum_{t=1}^{T} C_r^t(L)\epsilon_t \sum_{r=1}^{T}\epsilon_{t-r}\right] \end{aligned}$$

Simplifying we obtain

$$-E(\bar{x}_i'\bar{\epsilon}_i) = -\frac{1}{T^2}\sum_{t=1}^{T}\sum_{r=1}^{T} C_r^t \tag{9}$$

Equation (9) suggests that even if there is no causal effect of x on y, a fixed-effects regression of y on x could yield a spurious but statistically significant estimate of such an effect. The sign of the estimate will be the opposite that of the dynamically endogenous effect of past y on current x. Thus, under certain conditions, if we know the form of dynamic endogeneity we may be able to predict the bias in a fixed-effects regression that ignores dynamic endogeneity. If board independence is negatively related to past performance, then a fixed-effects estimate of board independence on firm performance in a static model will be positively biased. If board size is positively related to past performance, a fixed-effects regression of board size on firm performance will be negatively biased.

3.2 Dynamic panel GMM estimation

To obtain consistent and unbiased estimates, we estimate the relation between board structure and performance using a dynamic GMM panel estimator. This estimator was introduced by Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991), and further developed in a series of

[4] See Roodman (2008). Roodman (2008) also derives the potential biases from fixed-effects regressions of y on leads or lags of x for the model specified in (7)

papers including Arellano and Bover (1995) and Blundell and Bond (1998). It exploits the dynamic endogeneity inherent in our explanatory variables. The dynamic modeling approach has been used in other areas of economics where the structure of the problem suggests a dynamic relation between dependent and independent variables. Examples include measuring economic growth convergence (Caselli, Esquivel, and Lefort (1996), estimating a labor demand model (Blundell and Bond (1998)), and estimating the relation between financial intermediary development and economic growth (Beck, Levine, and Loayza (2000)).

The basic estimation procedure consists of two essential steps. First, we write the dynamic model of (2) in first-differenced form:

$$\Delta y_{it} = \alpha + \kappa_p \sum_p \Delta y_{it-p} + \beta \Delta \mathbf{X}_{it} + \gamma \Delta \mathbf{Z}_{it} + \Delta \epsilon_{it}, \quad p > 0 \tag{10}$$

First differencing eliminates any potential bias that may arise from unobserved heterogeneity. After first-differencing, we estimate (10) via GMM using lagged values of the explanatory variables as instruments for the current explanatory variables. That is, we use historical values of performance, board structure and other firm-specific variables as instruments for current changes in these variables.

An important aspect of the dynamic panel estimator is its use of the firm's history as instruments for our explanatory variables. This means that in estimating equation (2) or the first-difference transformation in equation (10), our instruments will be drawn from the set of lagged dependent or explanatory variables, i.e, $y_{t-k}, \mathbf{X}_{t-k}, \mathbf{Z}_{t-k}$, where $k > p$. For these instrument to be valid, they must meet two criteria. First, they must provide a source of variation for current governance, i.e., $\mathbf{X}_t = f(y_{t-k}, \mathbf{X}_{t-k}, \mathbf{Z}_{t-k})$. In our discussion on the determinants of board structure we have already established a theoretical motivation for this assumption. In additional analysis and using a variety of empirical tests in section 5, we show that board structure is strongly correlated to historical performance and lagged values of other explanatory variables.

Second, the historical or lagged values must provide an *exogenous* source of variation for current governance. This means that lagged variables must be uncorrelated with the error in the performance equation in equation (2). Theory provides motivation for this. As discussed earlier, if

the board structure that we observe today is one that trades off the anticipated costs and benefits of particular board structures, then current shocks to performance must have been unanticipated when the boards were chosen. Any information from the firm's past is impounded into current expected performance within p time periods. This means that p lags of past performance are sufficient to capture the influence of the firm's past on the present – i.e., including p lags ensures *dynamic completeness* of (2). Provided we have included p lags of performance, any information from the firm's history that is older than that has no direct effect on current performance and only affects performance through its effect on current governance and other firm characteristics. Thus, the firm's history beyond period $t - p$ should be *exogenous* with respect to any shocks or surprises in the current or future periods. In our empirical analysis, we further examine the validity of these exogeneity assumptions using a battery of empirical tests.

If the exogeneity assumptions are valid, then we can write the following orthoganlity conditions:

$$E(\mathbf{X}_{it-s}\epsilon_{it}) = E(\mathbf{Z}_{it-s}\epsilon_{it}) = E(y_{it-s}\epsilon_{it}) = 0, \qquad \forall\ s > p \tag{11}$$

We can then estimate (10) using GMM and the given orthogonality conditions. However, despite the economic appeal of this procedure, it does have at least three econometric shortcomings. First, Beck, Levine, and Loayza (2000)) note that if the original model is conceptually in levels, differencing may attenuate the signal to noise ratio and reduce the power of our tests. Second, Arellano and Bover (1995) suggest that variables in levels may be weak instruments for first-differenced equations. Third, first-differencing may exacerbate the impact of measurement errors on the dependent variables (Griliches and Hausman (1986)).

Arellano and Bover (1995) and Blundell and Bond (1998) argue that we can mitigate these shortcomings and improve the GMM estimator by also including the equations in levels in the estimation procedure. We can then use the first-differenced variables as instruments for the equations in levels in a "stacked" system of equations that includes the equations in *both* levels and differences. This produces a "system" GMM estimator, that involves estimating the following system:

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = \alpha + \kappa \begin{bmatrix} y_{it-p} \\ \Delta y_{it-p} \end{bmatrix} + \beta \begin{bmatrix} \mathbf{X}_{it} \\ \Delta \mathbf{X}_{it} \end{bmatrix} + \gamma \begin{bmatrix} \mathbf{Z}_{it} \\ \Delta \mathbf{Z}_{it} \end{bmatrix} + \epsilon_{it} \tag{12}$$

Unfortunately, the equations in levels still include unobserved heterogeneity. To deal with this, we assume that while the governance and control variables may be correlated with the unobserved effects, this correlation is constant over time. This is a reasonable assumption over a relatively short time period if the unobserved effects proxy for factors like unobserved director ability, managerial productivity, etc. The assumption leads to an additional set of orthogonality conditions:

$$E[\Delta \mathbf{X}_{it-s}(\eta_i + \epsilon_{it})] = E[\Delta \mathbf{Z}_{it-s}(\eta_i + \epsilon_{it})] = E[\Delta y_{it-s}(\eta_i + \epsilon_{it})] = 0, \qquad \forall \ s > p \tag{13}$$

With the system GMM estimator we obtain efficient estimates while controlling for unobserved heterogeneity, simultaneity and dynamic endogeneity.

We carry out GMM panel estimation using the orthogonality conditions of (11) and (13) under the assumption that there is no serial correlation in the error term, ϵ. The orthogonality conditions of (11) and (13) imply that we can use lagged levels as instruments for our differenced equations and lagged differences as instruments for the levels equations respectively. Later, we carry out rigorous tests of the validity of the orthogonality assumptions as well as the strength of the instruments that are implied by these assumptions.

3.3 Illustrating the bias in OLS and fixed-effects regressions driven by dynamic endogeneity

Above, we note that OLS and fixed-effects will be biased if our explanatory variables are not strictly exogenous and the panel's time dimension is small. In this section, we use a numerical simulation to illustrate this bias and to show the power and unbiasedness of the system GMM estimator.

Consider the case where the true model (data generating process) for firm performance (y_{it}) is:

$$y_{it} = \beta x_{it} + \gamma z_{it} + \eta_i + \varepsilon_{it}, \qquad \varepsilon_{it} \sim N(0, \sigma_e^2) \tag{14}$$

In this model, performance, y_{it}, is determined by an endogenous governance factor, x, a strictly exogenous factor, z, and an unobservable firm-specific factor, η. z is strictly exogenous in the sense that it does not depend on past performance or the unobservable firm factor.

The endogenous governance factor is determined by the process:

$$x_{it} = \alpha x_{it-1} + \pi z_{it} + \lambda y_{it-1} + \delta \eta_i + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma_e^2) \tag{15}$$

In this model, x is endogenous in two dimensions. First, it exhibits dynamic endogeneity because it relates to past performance, y, through λ. Parameter λ captures the key aspect of dynamic endogeneity. Second, x is also correlated with the unobserved firm specific factor, η. Thus, any estimation of equation (14) needs to account for both dynamic endogeneity and unobserved heterogeneity. The researcher, unaware of the true model, estimates equation (14) to draw inferences based on the magnitude and significance of the estimated coefficient, $\hat{\beta}$.

We simulate the system given by (14) and (15) and generate panel data sets of time and cross-sectional dimensions that are typical in corporate governance research ($T = 5$ and $N = 500$). We then estimate (14) using OLS, fixed-effects and Arellano and Bond (1991)'s dynamic GMM estimator.

Table 2 reports the results. We generate data using the following parameters: $\gamma = 0.6$, $\kappa = 0.9$, $\alpha = 0.7$, $\pi = 0.2$, $\delta = 0.5$, and a range of values for the dynamic adjustment factor, λ. We report results for different values of λ since this essentially captures the dynamic nature of the panel. The reported coefficients and standard errors are based on 1,000 replications.

Panel A of Table 2 shows the simulation results when the true $\beta = 0$. In this scenario, the truth is that governance does not impact performance. However, OLS and fixed-effects' estimates are significantly biased, producing a spurious correlation between governance and firm performance. For example, when the true β is zero and there is a modest amount of dynamic endogeneity ($\lambda = -0.1$), fixed-effects estimation produces a statistically significant estimate of 0.3787 with a 0.0740 standard error in a sample where $T = 5$. Both OLS and fixed-effects, ignoring dynamic endogeneity, lead us to wrongly infer that governance affects performance. We also observe the "sign flip" in the fixed-effects estimate: the OLS bias is opposite the fixed-effects bias. When the explanatory

variable, x, is negatively (positively) related to past values of the dependent variable, y, a fixed-effects regression of y on x yields a positive (negative) coefficient on x.

In every case where $\lambda \neq 0$, the estimates of $\hat{\beta}$ from OLS and fixed-effects are biased. OLS estimates are biased largely because of unobserved heterogeneity. The fixed-effects estimates appear less biased than those of OLS estimates because fixed-effects eliminates the unobserved heterogeneity; however, they are still biased due to dynamic endogeneity. Only in the singular case when $\lambda = 0$ (in which case, there is no dynamic 'feedback') are the fixed-effects estimates unbiased. Although the bias of the fixed-effects estimates decreases as T increases, we need a long time series to completely eliminate the bias. For example, Judson and Owen (1999) show that even when T is 30, the bias of the fixed-effects estimator can still be quite large and significant. However, most corporate governance studies have limited time-series; typically, $T < 10$.[5]

In contrast to OLS and fixed-effects, Panel A of Table 2 shows that Arellano and Bond (1991)'s dynamic GMM estimator produces unbiased results regardless of the magnitude of λ. For example, when the true β is 0, but there is dynamic endogeneity ($\lambda = -0.8$, the dynamic GMM estimate of the true beta is an insignificant 0.0054.

In Panel B of Table 2, we report results for when the true β is non-zero ($\beta = 0.3$ in this case) to demonstrate the power of the GMM estimator. Again we find that we find that the dynamic GMM procedure yields unbiased estimates of the true β, while both OLS and fixed-effects estimation result in biased inferences. In additional untabulated simulations we find that the GMM estimator is able to unbiasedly detect β when it is as low as 0.03.

Overall, the numerical simulations illustrate the pitfalls inherent in ignoring dynamic endogeneity and unobserved heterogeneity in panel data samples. They also illustrate the relative power and unbiasedness of the GMM dynamic estimator when the variable of interest adjusts to past realizations of the dependent variable. A further benefit of the GMM procedure is that it does not require detailed knowledge of the dynamic process that generates the endogenous variable in order to produce consistent and unbiased results. As long as theory suggests a dynamic process with un-

[5]For example, studies of governance and ownership that have relied on panels include Yermack (1996) where T=7 and Himmelberg, Hubbard, and Palia (1999) where T=10. In unreported simulations we find that the bias in the fixed effect estimates persist even when T is as high as 20.

observable fixed-effects, all that the GMM procedure needs is lagged values of the dependent and explanatory variables, which are used as instruments in the GMM estimation procedure.

Next, we examine the relation between performance and board structure using actual data, and compare the results of OLS and fixed-effects estimates (used in prior studies) to those obtained with dynamic GMM estimation.

4 Data, Sample Selection and Variables

In this section we describe the data for the empirical settings that we use to illustrate the impact of dynamic endogeneity in corporate finance: (1) the relation between board structure and firm performance and (2) the determinants of board structure.

4.1 Data and Sample Selection

Board structure is highly persistent. This can attenuate the signal-to-noise ratio and reduce the power of any panel data estimator (see, for example, Zhou (2001)). Dynamic estimation also requires that we assume transient errors are uncorrelated. To mitigate these concerns, we sample at two-year intervals instead of every year, using governance data from 1991, 1993, 1995, 1997, 1999, 2001 and 2003.

We use the board data from Linck, Netter, and Yang (2008), which they collected from the DISCLOSURE database. DISCLOSURE is a comprehensive database of over 7,000 firms starting in 1991. Since our empirical tests include a number of control variables, we match the DISCLOSURE data with data from CRSP and COMPUSTAT, leaving a sample of more than 6,000 unique firms and over 16,000 firm-years. To our knowledge, this is the largest panel to date that has been used to study the performance/governance relationship. Table 3 reports summary statistics of our board and control variables. To avoid sample selection issues we do not require a balanced panel; thus, the number of firms differs each year – the estimation strategy uses as all available observations. The sample includes both large and small firms, unlike most previous studies that tend to focus on either large or small firms.

4.2 Measuring firm performance

The primary performance measure we use is return on assets (ROA), where ROA is defined as operating income before depreciation (COMPUSTAT item #13) divided by fiscal year end total assets (COMPUSTAT item #6). We also estimate industry adjusted ROA, which is the firm's ROA less the industry median ROA, defining industry by the 2-digit SIC code.

Many studies that examine the governance/performance relation use Tobin's Q as a measure of firm performance. This can be a problem for a number of reasons. Tobin's Q (usually defined as the market-to-book ratio) is a proxy for growth opportunities, and there is strong theoretical reason to expect that growth opportunities are a cause, rather than a consequence, of governance structures. Boone, Field, Karpoff, and Raheja (2007), Linck, Netter, and Yang (2008) and Lehn, Patro, and Zhao (2008) provide empirical evidence to support this notion. Thus, we use market-to-book as a control variable rather than a performance measure. However, for robustness and for comparison with existing research, we estimate models using Tobin's Q as a performance measure. Further, we also replicate our results using return on sales (ROS) as a performance measure to assess whether our results are sensitive to the specific performance measures we select.

4.3 Governance variables

We consider the effect of past performance on three board structure variables – board size, board composition and board leadership, which we define as follows:

- $LogBSIZE$, the logarithm of the number of directors on the board.
- $INDEP$, the proportion of outside (non-executive) directors on the board.
- CEO_CHAIR, a dummy variable equal to 1 if the CEO is also the chairman of the board.

4.4 Control variables

Recent studies (Raheja (2005), Coles, Daniel, and Naveen (2008), Boone, Field, Karpoff, and Raheja (2007) and Linck, Netter, and Yang (2008)) suggest that firms will choose their board structures based on the relative costs and benefits of each governance mechanism. The firm's chosen board structure will reflect the monitoring costs and private benefits of control the firm faces, as

well as the scope and complexity of its operations. Thus, as suggested by prior research, we use size, age, the number of business segments, growth opportunities, and leverage as determinants of board structure. Specifically, we define our control variables as follows:

- $LogMVE$, logarithm of the market value of equity.
- MTB, ratio of market-to-book value. This is obtained as market value of equity *plus* book value of assets *minus* book value of equity *minus* deferred taxes, all *divided* by book value of assets.
- $RETSTD$, standard deviation of (the past twelve months) of the firm's stock returns.
- $LogAGE$, the logarithm of the firm's age, where age is computed from the time the firm first appears on CRSP.
- $LogSEGMENTS$, the logarithm of the number of business segments.
- $DEBT$, the ratio of the firm's long-term debt to total assets.

Since these variables might also be related to firm performance, they serve as control variables in our empirical specification of firm performance as well.

5 The relation between board structure and firm performance

In this section, we examine the empirical relation between board structure and firm performance using the dynamic model developed above. In section 5.1, we determine how many lags of performance we need to ensure dynamic completeness. In 5.2, we present direct empirical evidence of the dynamic endogeneity of board structure. In section 5.3, we estimate the relation between board structure and firm performance using the dynamic panel GMM estimator. We compare the results to estimates obtained from a static model in order to understand biases that arise from ignoring different aspects of endogeneity. Finally, in section 5.4, we rigorously examine the validity of the instrument set that we use in the dynamic GMM estimation; i.e., we examine the strength and exogeneity of using the firm's history as instruments for current governance.

5.1 How many lags of performance are needed to ensure dynamic completeness?

Empirically it is important to understand how many lags of performance we need to capture all information from the past. This is important for at least two reasons. First, failure to capture all influences of the past on the present could still mean that equation (2) is mis-specified (i.e., there might be an omitted variable bias). Second, and perhaps more importantly, we argue that all older lags are exogenous with respect to the residuals of the present; thus, they can be used as instruments. This is important for consistent estimation using the dynamic panel GMM estimator.

Glen, Lee, and Singh (2001) and Gschwandtner (2005) suggest that two lags is sufficient to capture the persistence of profitability. Thus, we propose including two lags in our estimates of the performance/governance relation (i.e., we set $p = 4$ in equation (2) since our data is sampled every two years). To see if two lags are sufficient to ensure dynamic completeness, we estimate a regression of current performance on *four* lags of past performance, controlling for other firm-specific characteristics. Table 4 shows the results. We use two profitability measures: return on assets (*ROA*) and return on sales (*ROS*). Results suggest that including two lags is sufficient to capture the dynamic endogeneity of the governance/performance relation. In columns (1) and (3) the first two lags are statistically significant while older lags are insignificant. In columns (2) and (4) we drop the recent lags and include only the older lags. In these specifications, the older lags are statistically significant. Thus, while the older lags include relevant information, that information is subsumed by the more recent lags.

5.2 How strongly is the present correlated with the past?

A central argument in our paper is that board structure (size and independence) and other firm-specific variables are related to past performance. We examine this assertion directly with a series of tests. Our first set of tests involve OLS regressions of (1) current *levels* of board size, independence and other firm specific variables and (2) *changes* in these levels on past performance and historical values of the firm-specific variables.

The results are shown in Table 5. In panel A, we present results from OLS regressions of the *levels* of board structure and other firm characteristics on performance and characteristics from two

years before. We find that board independence is significantly negatively related to past performance as shown by Hermalin and Weisbach (1998). We also find that board size is significantly positively related to past performance, although the significance level drops when we control for past firm size. Further, current board size is significantly positively related to past firm size, and firm size is significantly related to past performance. The results suggest that firms that have done well in the past will be larger today and as a result will have bigger boards, as suggested by Fama and Jensen (1983) and documented by Boone, Field, Karpoff, and Raheja (2007), Coles, Daniel, and Naveen (2008) and Linck, Netter, and Yang (2008).

Panel B of Table 5 shows the results from OLS regressions of *changes* in board structure and firm characteristics on the levels performance and characteristics from two years before. The results are similar to those obtained from using the levels as dependent variables. Changes in board independence are negatively related to past performance, while changes in board size are positively related to past performance. Again we find that changes in board size in response to past performance is through the effect of performance on firm size.

Table 5 also shows that even the potential control variables are dynamically endogenous. Current levels and changes in market-to-book (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), firm age ($LogAGE$) and leverage ($DEBT$) are all significantly related to past performance. This highlights the fact that it is not only corporate governance that can be considered endogeneous, but *all* the control variables that we may want to use as proxies for the firm's operating and contracting environment are likely to be endogenous as well.

We carry out a second test of strict exogeneity suggested by Wooldridge (2002). If $\mathbf{X}_{i,t}$ contains the explanatory governance and control variables, we can test for strict exogeneity by estimating the following fixed-effects model:

$$\mathbf{y}_{i,t} = \alpha + \beta \mathbf{X}_{i,t} + \Omega \mathbf{W}_{i,t+2} + \eta_i + \varepsilon_{it}, \qquad t = 1991, 1993, 1995, \ldots, 2001 \tag{16}$$

where $\mathbf{W}_{i,t+2}$ is a subset of future values of the corporate governance and control variables. Under the null hypothesis of strict exogeneity, $\Omega = 0$. i.e., future realizations of our governance and

control variables are unrelated to current performance.

Table 6 shows the results of estimating (16), with different subsets of the governance and control variables, $\mathbf{W}_{i,t+2}$. In every specification in which they are included, the coefficient estimates for the future vales of both board size ($LogBSIZE_{t+2}$) and CEO as board chair (CEO_CHAIR_{t+2}) are significantly different from zero. This suggests that neither of these board variables are strictly exogenous and instead adjust in response to firm performance. In addition, the coefficient estimates on the future values of some control variables ($LogMVE_{t+2}$, $RETSTD_{t+2}$ and $DEBT_{t+2}$) are also significantly different from zero, suggesting that these variables also adjust to firm performance. An F-test of the joint significance of the coefficient estimates of all the futures values is also significant.

Overall, the results from Table 6 suggest that neither the board structure nor the firm control variables are strictly exogenous, and confirms both our theoretical predictions and the results from the OLS regressions in Table 5.

5.3 The relation between board structure and current firm performance

In this section, we examine the results from estimating the relation between board structure and current firm performance. In order to compare to past research and highlight the potential problems from ignoring dynamic endogeneity, we estimate the following models:

1. An OLS model
2. A fixed-effects model
3. A dynamic OLS model
4. A dynamic fixed-effects model (System GMM)[6]

[6]An intuitive way of thinking about the dynamic model is that it is essentially an empirical estimate of the following dynamic simultaneous equation model:

$$\begin{bmatrix} y_t \\ \mathbf{X}_t \\ \mathbf{Z}_t \end{bmatrix} = \begin{bmatrix} y \\ x \\ z \end{bmatrix} + \begin{bmatrix} 0 & y2 & y2 & 0 \\ x0 & x2 & x4 & x6 \\ z0 & z2 & z4 & z6 \end{bmatrix} \begin{bmatrix} y_t \\ y_{t-2} \\ y_{t-4} \\ y_{t-6} \end{bmatrix} + \begin{bmatrix} y0 & 0 & 0 & 0 \\ 0 & x2 & x4 & x6 \\ 0 & z2 & z4 & z6 \end{bmatrix} \begin{bmatrix} \mathbf{X}_t \\ \mathbf{X}_{t-2} \\ \mathbf{X}_{t-4} \\ \mathbf{X}_{t-6} \end{bmatrix}$$
$$+ \begin{bmatrix} y0 & 0 & 0 & 0 \\ 0 & x2 & x4 & x6 \\ 0 & z2 & z4 & z6 \end{bmatrix} \begin{bmatrix} \mathbf{Z}_t \\ \mathbf{Z}_{t-2} \\ \mathbf{Z}_{t-4} \\ \mathbf{Z}_{t-6} \end{bmatrix} + \begin{bmatrix} \ \end{bmatrix} + \begin{bmatrix} yt \\ xt \\ zt \end{bmatrix}$$

where y_t is firm performance, $\mathbf{X}_t$ contains the governance variables and $\mathbf{Z}_t$ contains the firm characteristics. The

Table 7 reports the results when we use return on assets (ROA) as our performance measure. As we discussed earlier, we include two lags of performance in the dynamic model. This makes historical performance and historical firm characteristics, lagged three periods or more, available for use as instruments. We use variables lagged three and four periods ($t-6$ and $t-8$, respectively, since we sample at two-year intervals) as instruments for all the endogenous variables in the GMM estimates.[7] Our assumption in the GMM regression is that all the regressors except firm age and the year dummies are endogenous.

Static OLS and fixed-effects estimates suggest a *negative* relation between board size and firm performance. This finding is similar to those obtained by a number of prior studies including Yermack (1996), Eisenberg, Sundgren, and Wells (1998) and Bhagat and Black (2002). However, once we move to a dynamic model, these results disappear. In a simple dynamic OLS model, board size is no longer significantly related to firm performance. For example, the coefficient on board size is a significantly negative -0.0262 ($t = 5.76$) using a static OLS model, but is insignificant in the dynamic OLS model that includes lagged performance (-0.0033, $t = -0.73$). While the simple dynamic OLS model is an improvement over the static models, it is merely an intermediate step.[8] It is likely that there is some unobservable heterogeneity that is not captured by past performance. The system GMM model enables us to estimate the governance/performance relation while including *both* past performance *and* fixed-effects to control for dynamic endogeneity and unobservable heterogeneity respectively.

The results show that when we include fixed-effects in a dynamic model and estimate via system GMM, the coefficient on board size is insignificant (0.0183, $t = 0.43$). This is in sharp contrast to the results from the static fixed effect model in which the coefficient on board size is significantly negative (-0.0261, $t = -4.52$). However, the negative bias in the fixed-effects' coefficient estimate

essential difference between the OLS and the System GMM estimates is that OLS requires the restrictive assumption that ${}_{x0} = {}_{z0} = 0$, i.e., no simultaneity and that $= 0$, i.e., no unobservable heterogeneity. See Holtz-Eakin, Newey, and Rosen (1988) for a discussion of this concept.

[7] See the appendix for further details of the system GMM estimation using xtabond2 in STATA 9. The large number of endogenous variables means that we have many instruments and could inadvertently overfit our endogenous variables. To reduce the this possibility we use the "collapse" option in xtabond2. However, as an additional robustness check we conduct our analysis with all the instruments dated $t-6$ or later. The results are quantitatively and qualitatively unchanged.

[8] Note that the R^2 improves from 27% in the static OLS model to 41% in the dynamic OLS model, suggesting that past performance adds explanatory power.

is consistent with the bias we expect to have if we ignore dynamic endogeneity: if board size is positively related to past performance, then fixed-effects estimates of the relation between board size and firm performance will be negatively biased.

The static OLS estimate also suggests a negative relation between board independence and firm performance (-0.0266, $t = -3.56$), similar to that reported in a number of prior studies including Yermack (1996), Klein (1998) and Bhagat and Black (2002). Interestingly, when we estimate this in a static fixed-effects' model, the sign flips to positive and significant (0.0202, $t = 2.48$). However, in both the dynamic OLS model and the dynamic GMM model, the relation between board independence and firm performance is insignificant (0.0061, $t = 0.82$ and -0.0109, $t = -0.14$, respectively). Again, the positive bias in the static fixed-effects estimates is the bias we expect would be introduced if we ignore dynamic endogeneity: if board independence is negatively related to past performance, then fixed-effects estimates of the relation between board independence and firm performance will be positively biased.

5.4 Assessing the validity of instruments used in GMM estimation

The consistency of the coefficient estimates obtained with the dynamic panel GMM estimator depends, to a significant extent, on the validity of the instruments that we use. In section 3.3, we made an economic argument for the exogeneity and relative strength of our instruments. In this section, we discuss econometric tests to assess these characteristics.

5.4.1 Exogeneity of instruments

Our key exogeneity assumption, as stated in equation (8), is that the firm's historical performance and characteristics are exogenous with respect to current shocks or innovations in performance. Arellano and Bond (1991) suggests two tests of this assumption.

The first test is a test of serial correlation. The biggest concern is whether or not we have included enough lags to control for dynamic endogeneity. If we have, then any historical value of firm performance beyond those lags is a potentially valid instrument since it will be exogenous to current performance shocks. Table 7 shows the results of $AR(1)$ and $AR(2)$ tests of the null hypothesis of no first or second order serial correlation, respectively. For our GMM estimates, if the

assumptions of our specification are valid, by construction the residuals in first differences ($AR(1)$) should be correlated, but there should be no serial correlation in second differences ($AR(2)$). Results of these tests confirm that this is the case: the $AR(1)$ test yields a p-value of < 0.01 and the $AR(2)$ test yields a p-value of 0.87.

The second test is a Hansen test of over-identification. The dynamic panel GMM estimator uses multiple lags as instruments. This means that our system is over-identified and provides us with an opportunity to carry out the test of over-identification. Table 7 shows the results of the Hansen test for our GMM estimates. The Hansen test yields a J-statistic which is distributed χ^2 under the null hypothesis of the validity of our instruments. The results in Table 7 reveal a J-statistic with a p-value of 0.41 and as such, we cannot reject the hypothesis that our instruments are valid.

In Table 7 we also report the results from a test of the exogeneity of a subset of our instruments. As we discussed in section 3.3, the system GMM estimator makes an additional exogeneity assumption: the assumption that any correlation between our endogenous variables and the unobserved (fixed) effect is constant over time (equation (10)). This is the assumption that enables us to include the levels equations in our GMM estimates and use lagged differences as instruments for these levels. Bond, Hoeffler, and Temple (2001) suggest that this assumption can be tested directly using a difference-in-Hansen test of exogeneity. This test also yields a J-statistic which is distributed χ^2 under the null hypothesis that the subset of instruments that we use in the levels equations are exogenous. The results in Table 7 show a p-value of 0.23 for the J-statistic produced by the difference-in-Hansen test. This implies that we cannot reject the hypothesis that the additional subset of instruments used in the system GMM estimates is indeed exogenous.

Taken together, the specification tests provide empirical verification for our argument that historical firm performance and other firm characteristics are indeed exogenous with respect to current shocks to performance and can be used as valid instruments.

5.4.2 Strength of instruments

A number of authors (e.g. Bound, Jaeger, and Baker (1995), Staiger and Stock (1997), Stock and Yogo (2005)) have shown that if the endogenous variables are only weakly correlated with

the instruments, estimates from an IV regression could be biased. As far as we know, there is no single criteria for evaluating the joint strength of the instrument set of the dynamic panel system GMM estimator. However, Staiger and Stock (1997) and Stock and Yogo (2005) outline a process, and develop a set of critical values, for evaluating the strength or weakness of instruments in a standard two-stage least squares (TSLS) regression. We adapt these to assess the strength of the instruments we use in our GMM estimates. The process involves two tests. First we carry out a first-stage regression of our endogenous variables on the instruments and examine the F-statistics. Second, we compute a Cragg-Donald statistic, which may be more informative than the F-statistics from the first stage regressions if we have more than one endogenous variable. We compare this to critical values for instrument weakness developed by Stock and Yogo (2005).

If y is performance and $\mathbf{X}$ includes all the regressors, system GMM involves estimating the following:

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = \alpha + \beta \begin{bmatrix} \mathbf{X}_{it} \\ \Delta \mathbf{X}_{it} \end{bmatrix} + \epsilon_{it} \tag{17}$$

To assess the strength of our instruments we split our system into its constituent levels and difference equations. We separately assess the strength of: (1) lag differences as instruments in the level equations and (2) lagged levels as instruments in the differenced equations. First, we examine the equations in levels:

$$y_{it} = \alpha_l + \beta_l \mathbf{X}_{it} + \nu_{it} \qquad \text{Instruments: } \Delta \mathbf{X}_{it-4} \tag{18}$$

and the equation in differences:

$$\Delta y_{it} = \alpha_d + \beta_d \Delta \mathbf{X}_{it} + \varepsilon_{it} \qquad \text{Instruments: } \mathbf{X}_{it-6} \tag{19}$$

Table 8 shows the results of our analysis. For the variables in levels, we obtain the F-statistics by regressing each variable on all the lagged differences used as instruments ($\Delta \mathbf{X}_{it-4}$). Similarly, for the variables in differences, we obtain the F-statistics by regressing each variable on all the lagged levels used as instruments ($\mathbf{X}_{it-6}$). To obtain the Cragg-Donald statistic, we carry out two separate two-stage least squares regresions, one each for the levels and differenced equations respectively.[9]

[9] Using the ivreg2 module in STATA 9

It is worth noting that for the system GMM regressions, these tests are merely indicative of the strength of the instruments since consistency of the GMM estimates relies on the *joint* estimation of both the levels and the difference equations.

Table 8 shows that F-statistics for all the first stage regressions are significant, which implies that the instruments provide significant explanatory power for the endogenous variables. With only one exception, the F-statistics are all bigger than 10, which is the "rule of thumb" critical value suggested by Staiger and Stock (1997) for assessing instrument strength.

Finally, we examine the Cragg-Donald statistics. For the levels equations, the Cragg-Donald statistic is 22.60. This value exceeds *all* the critical value from Table 5.1 of Stock and Yogo (2005), implying that any bias from using the instruments is less than 5% of the bias from an OLS regression, with a 5% level of significance. For the differenced equations the Cragg-Donald statistic of 4.29 lies just below the critical value (4.37)[10] at which level we can be confident (with a 5% level of significance) that the bias from the two-stage least squares estimates is less than 30% of the bias from an OLS regression.

Overall, the results from our test of the strength of our instruments leaves us confident that the results of our GMM estimates are not been driven by weak instruments.

5.5 Alternative measures of firm performance

We re-estimate the relation between firm performance and board structure using two alternative performance measures – return on sales and Tobin's Q. Return on sales is defined as operating income divided by total sales. We also compute an industry adjusted ROS for each firm, which is the individual firm *ROS* less the median industry ROS, where industry is defined by the 2-digit SIC code. Tobin's Q is the market value of equity *plus* book value of assets *minus* book value of equity *minus* deferred taxes, all *divided* by book value of assets.

The first two columns of Table 9 show the results of static fixed-effects and dynamic GMM estimates using return on sales (ROS) as the measure of a firm performance. The results are similar to those obtained when we use return on assets (ROA). The fixed-effects regression shows a negative relation between board size and firm performance; however, the coefficient is insignificant with

[10]This is the critical value when $K = 15$, which is the number of instruments in the equation

GMM estimation. The fixed-effects regression also shows a positive relation between independence and firm performance. Again, using GMM estimation we find no relation between independence and performance. As with *ROA*, the biases we observe are consistent with the biases we expect to be induced from ignoring dynamic endogeneity.

Table 9 also shows the results from using Tobin's Q as the performance measure. Earlier we argue that Tobin's Q is likely to be a problematic measure of firm performance when examining the effect of board structure variable on performance. This is because market-to-book (the most commonly used proxy for Q) likely reflects a firm's growth opportunities, and prior research suggests that growth opportunities affect board structure. However, if we assume that growth opportunities are likely to be common across industries, using an industry-adjusted market-to-book value as a proxy for Tobin's Q may help to separate the "performance" component of Tobin's Q from the "growth opportunities" component.

The last two columns of Table 9 show the results of static and dynamic (System GMM) fixed-effects estimates using Tobin's Q as the performance measure. The results are similar to those obtained from using *ROA* and *ROS*. The fixed-effects regression that ignores dynamic endogeneity suggests a negative relation between board size and firm performance and a positive relation between independence and firm performance. Again we see that once we control for dynamic endogeneity and estimate the relation using System GMM, we find no relation between any board variables and firm performance. Past performance is the only significant determinant of current performance.

6 The determinants of board structure in a dynamic framework

Our analysis thus far has focused on identifying the effect of board structure on firm performance. The analysis itself assumes that the firm characteristics that we have identified as proxies for the firm's operating and contracting environment (size, growth opportunities, risk, age and leverage) are actual determinants of board structure. In other words, we have assumed that the *exogenous* components of these characteristics have a causal effect on board structure. While there is strong empirical evidence in the literature suggesting that this is the case (e.g. Boone, Field, Karpoff, and

Raheja (2007), Linck, Netter, and Yang (2008) and Lehn, Patro, and Zhao (2008)), these studies do not all control for all the major sources of endogenity in the board/structure performance relation that we have identified here: simultaneity, unobservable heterogeneity and dynamic endogeneity.

In this section we examine whether firm characteristics are determinants of board structure using a dynamic model and applying the dynamic GMM panel estimator. We estimate an empirical model of the form:

$$x_{it} = \alpha + \sum_s \kappa_s x_{it-s} + \gamma \mathbf{Z}_{it} + \eta_i + \epsilon_{it} \quad s = 1, \ldots, p \tag{20}$$

where x is either board size or independence and $\mathbf{Z}_{it}$ is a vector of firm characteristics that includes firm performance. Table 10 shows the the results and compares the results obtained from the dynamic panel GMM estimator with those obtained using OLS.

The GMM results show that even after controlling for simultaneity, unobservable heterogeneity and dynamic endogeneity, firm size, growth opportunities, age and leverage are determinants of board structure – results similar to those obtained from OLS estimates of a static model and also similar to those obtained in recent studies such as those by Boone, Field, Karpoff, and Raheja (2007) and Linck, Netter, and Yang (2008).[11] However, this application also demonstrates the importance of controlling for both dynamic endogeneity and unobservable heterogeneity in the analysis. For example, the estimated magnitude of the effect of firm size on board size (independence) from GMM regressions, while still significant, is 66% (58%) smaller than the estimated magnitude of the effect from OLS regressions. Similarly, the estimated magnitude of the effect of firm age on board size (independence) from GMM regressions, while also still significant, is 65% (61%) smaller than the estimated magnitude of the effect from OLS regressions. This suggests that even in this context, OLS estimates may be biased upwards because of the combination of unobservable heterogeneity and dynamic endogeneity.

One fact that emerges from this analysis is that when we examine the determinants of board structure, our overall inference is unchanged when we move from OLS estimation of a static model to estimation using the dynamic GMM panel estimator. This is in sharp contrast to what we found

[11]Linck, Netter, and Yang (2008) report that their results are robust to the use of the dynamic panel GMM estimator

in our earlier analysis of the effect of board structure on performance where our inference changes significantly when we control for dynamic endogeneity. This difference may provide some insight as to what aspects of empirical corporate finance analysis may be the most susceptible to biases arising from ignoring the combination of unobservable heterogeneity and dynamic endogeneity, and correspondingly, where analysis using dynamic panel estimation may be most important. If we are interested in the effect of governance on performance (a "performance on structure" regression), dynamic endogeneity will be especially important since there is a strong relation between past values of the dependent variable (performance), and current values of the explanatory variables (governance or firm characteristics).

On the other hand, if we are interested in the effect of firm characteristics on governance (a "structure on structure" regression), then dynamic endogeneity may be less important. The explanatory variables (size, business segments etc) are not strongly determined by past values of the dependent variable (governance); any link from past governance to current firm characteristics will be indirect through the effect (if any at all) of governance on performance. While there is no doubt a strong relation that exists between past characteristics (such as size or number of segments) and current board structure, the argument for the reverse is much weaker. Firms are not bigger today nor do they operate in more business segments merely because they had more board members in the past. Thus, when we measure the effects of firm characteristics on board structure, we should draw similar inferences from either OLS or dynamic GMM estimates, which is what the results in Table 10 suggest.

7 Conclusion

Corporate finance research, which estimates the causes and effects of financial decisions, has potential problems with endogeneity since it is generally difficult to find exogenous factors to identify the empirical relationships being studied. For example, while a large body of research suggests that certain governance structures drive improved performance, this research is plagued with endogeneity concerns. In this paper, we examine how dynamic endogeneity – the idea that the relation among a firm's observable characteristics is likely to be dynamic – impacts research efforts to measure

the causal relation between governance and firm performance. In the governance/performance context, a firm's current performance affects both future governance and future performance. Intuitively, the key notion is that a major determinant of a firm's governance and contracting environment is the firm's history and past performance, and that failure to account for this may lead to biased inferences. The reason is that the firm's historical performance may proxy for important attributes, such as managerial ability, that are otherwise unobservable and that affect future decisions and performance.

The contribution of this paper is two-fold. First, we show how controlling for dynamic endogeneity results in well-specified and powerful empirical tests of the relation between governance and firm performance. It enables the researcher to improve their estimations, both theoretically and practically, by using instruments that are grounded in theory. We provide strong evidence that the instruments we develop are valid and powerful. We also include details on how to implement the procedure, which is relatively simple given readily available tools (e.g., STATA). Second, we apply this technique to two important questions: (1) the relation between board structure and performance and (2) the determinants of board structure. In a panel of 6,000 firms from 1991–2003, we find evidence of dynamic endogeneity. After controlling for it, we find no relation between board size or independence and firm performance. We show the results of earlier studies that do not account for dynamic endogeneity may be biased in a predictable way. As for the determinants of board structure, we find that the broad conclusions of existing research are relatively unaffected once we control for dynamic endogeneity. However, the magnitude by which various characteristics affect board structure may be overstated.

Our results help reconcile some of the conflicting results in the prior literature and explain how some reported correlations could arise from ignoring one or more aspects of the endogeneity inherent in the board structure/performance relation. For example, we argue that a negative relation between board independence and past firm performance induces a positive bias when measuring the effect of board independence on current firm performance with a static fixed-effects regression. Similarly, we predict and find a negative bias when measuring the effect of board size on firm performance from a fixed-effects regression given the positive relation we observe between board size

and past performance.

We believe that this methodology can improve the empirical estimations in many areas of corporate finance research. Our results offer a practical insight into what aspects of empirical corporate finance research may be the most susceptible to biases arising from ignoring the combination of unobservable heterogeneity and dynamic endogeneity, and correspondingly, where analysis using dynamic panel estimation may have the most impact on inference. Specifically, controlling for dynamic endogeneity will be particularly important in analyses where there is a strong relation between past values of the dependent variable, and current values of the explanatory variables. This is likely to be the case in models that involve estimating how various firm characteristics impact performance.

A Appendix

A.1 Dynamic Panel Estimation with GMM

The following discussion draws substantially from Bond (2002) and Roodman (2006).

Consider the dynamic unobserved effects model of equation (2):

$$y_t = y_{i,t-1} + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_{it} + \eta_i + \epsilon_{it} \tag{21}$$

A first difference transformation eliminates the unobserved effects and gives:

$$\Delta y_{it} = \Delta \mathbf{X}_{it} \beta + \Delta \epsilon_{it} \tag{22}$$

where $\mathbf{X}_t$ is a $T-1 \times K$ vector defined as $(y_{i,t-1}, \mathbf{x}_{it}, \mathbf{z}_{it})$ and Δ is the first difference operator.

Under the assumption of *sequential exogeneity* :

$$E(\epsilon_{it} | \mathbf{X}_{i,t-1}, \mathbf{X}_{i,t-2}, \ldots, \mathbf{X}_{i1}) = 0 \tag{23}$$

Sequential exogeneity implies that current shocks are independent of past values of the dependent variable, but leaves open the possibility that current and future values of the dependent variable might adjust to current shocks (*simultaneity* and *dynamic enodgenity*, respectively).

The sequential exogeneity assumption suggests the following set of orthogonality conditions for equation (25):

$$E(\mathbf{X}'_{is} \Delta \epsilon_{it}) = 0, \qquad s = 1, \ldots, t-2 \tag{24}$$

Arellano and Bond (1991) suggest that we can use these orthogonality conditions to obtain a GMM estimate of β. If we define a matrix of instruments, $\mathbf{Z}_i$:

$$\begin{pmatrix} \mathbf{X}_{i1} & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 \\ 0 & \mathbf{X}_{i2} & \mathbf{X}_{i1} & \cdots & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \mathbf{X}_{iT-2} & \cdots & \mathbf{X}_{i2} & \mathbf{X}_{i1} \end{pmatrix} \text{ or collapsed, } \begin{pmatrix} \mathbf{X}_{i1} & 0 & \cdots & 0 \\ \mathbf{X}_{i2} & \mathbf{X}_{i1} & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ \mathbf{X}_{iT-2} & \cdots & \mathbf{X}_{i2} & \mathbf{X}_{i1} \end{pmatrix} \tag{25}$$

we can do GMM based on:

$$E(\mathbf{Z}'_i \Delta \epsilon_i) = 0 \tag{26}$$

(28) means that we can use the following instruments for each first-differenced equation:

Equation	Instruments
$\Delta y_{i3} = \Delta \mathbf{X}_{i3}\beta + \Delta\epsilon_{i3}$	$\mathbf{X}_{i1}$
$\Delta y_{i4} = \Delta \mathbf{X}_{i4}\beta + \Delta\epsilon_{i4}$	$\mathbf{X}_{i1}, \mathbf{X}_{i2}$
$\vdots$	$\vdots$
$\Delta y_{iT} = \Delta \mathbf{X}_{iT}\beta + \Delta\epsilon_{iT}$	$\mathbf{X}_{i1}, \mathbf{X}_{i2}, \ldots, \mathbf{X}_{iT-2}$

The asymptotically efficient GMM estimator based on the moment conditions in (29) minimizes the criterion:

$$\left[\mathbf{Z}_i'(\Delta \mathbf{y}_i - \Delta \mathbf{X}_i)\right]' \hat{\mathbf{W}} \left[\mathbf{Z}_i'(\Delta \mathbf{y}_i - \Delta \mathbf{X}_i)\right] \tag{27}$$

The GMM estimator that minimizes this criterion is obtained as:

$$\hat{\beta}_{GMM} = \left[\left(\sum_i \Delta \mathbf{X}_i' \mathbf{Z}_i\right) \hat{\mathbf{W}} \left(\sum_i \Delta \mathbf{Z}_i' \mathbf{X}_i\right)\right]^{-1} \left(\sum_i \Delta \mathbf{X}_i' \mathbf{Z}_i\right) \hat{\mathbf{W}} \left(\sum_i \Delta \mathbf{Z}_i' \mathbf{y}_i\right) \tag{28}$$

where the optimal weighting matrix, $W = \Lambda^{-1}$, and $\Lambda = E(\mathbf{Z}_i' \Delta\epsilon_i \Delta\epsilon_i' \mathbf{Z}_i)$.

The GMM estimator described above is known as the "difference" GMM estimator. Arellano and Bover (1995) and Blundell and Bond (1998) suggests that we can improve on the "difference" GMM estimator using the "system" GMM estimator (see section 3.3 for a discussion of the shortcomings of the "difference" estimator). The "system" estimator requires carrying out GMM estimation using a "stacked" system consisting of both first-differenced and level equations.

The "system" GMM estimator does not directly eliminate the unobserved effect, but if we assume that the correlation between the unobserved effect and our explanatory variables is constant over the time period of our data set, we have the following additional set of orthogonality conditions:

$$E(\Delta \mathbf{X}_{it}\eta_i) = 0, \qquad t = 2, \ldots, T \tag{29}$$

We can use (32) to define a matrix of instruments for our level equations as follows:

$$\begin{pmatrix} \Delta \mathbf{X}_{i1} & 0 & \cdots & 0 \\ 0 & \Delta \mathbf{X}_{i2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \Delta \mathbf{X}_{iT-2} \end{pmatrix} \text{or collapsed,} \begin{pmatrix} \Delta \mathbf{X}_{i1} \\ \Delta \mathbf{X}_{i2} \\ \vdots \\ \Delta \mathbf{X}_{iT-2} \end{pmatrix} \tag{30}$$

(33) means that we can use the following instruments for each level equation:

Equation	Instruments
$y_{i3} = \mathbf{X}_{i3}\beta + \epsilon_{i3}$	$\Delta\mathbf{X}_{i1}$
$y_{i4} = \mathbf{X}_{i4}\beta + \epsilon_{i4}$	$\Delta\mathbf{X}_{i2}$
$\vdots$	$\vdots$
$y_{iT} = \mathbf{X}_{iT}\beta + \epsilon_{iT}$	$\Delta\mathbf{X}_{iT-2}$

A.2 Implementing Dynamic GMM estimation in STATA (Version 9)

Dynamic GMM estimation can be implemented in STATA using the `xtabond2` command. The following example illustrates the use of the `xtabond2` command. As is the case with other panel data estimators in STATA, `xtabond2` requires you to specify that your data is a panel by using the `tsset` command. See Roodman (2006) for comprehensive details of using `xtabond2`, the full range of options available and specifications tests.

Assume the data set consists of a dependent variable, `y` and two explanatory variables, `x1` and `x2`. One can obatin a “system" GMM estimate of the effects of `x1` and `x2` on `y` as follows:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag(a b)) <(options)>
```

The lagged dependent variable (`l.y`) is included as an explanatory variable as specified in (A.1). The `gmm` command invokes our lagged instrument set. `lag(a b)` indicates what lags we wish to include as instruments; `a` indicates the most recent lag we should use while `b` represents the most distant lag. If we think `x1` and `x2` are merely predetermined then we can set `a` as 1. However, if we assume that `x1` and `x2` are endogenous, then we can set `a` as 2 or greater. If we wish to use all the lags greater than `a`, then we can write our `xtabond2` command as:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag(a .)) <(options)>
```

This command essentially invokes the instrument set described by (28) and (33) above.

If we are willing to assume that we have a *strictly exogenous* variable (say, `z`), `xtabond2` allows us to partition our dependent variables (in the spirit of Hausman and Taylor (1981)) into endogenous and exogenous variables, using `` `gmmstyle' `` and `` `ivstyle' `` commands:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag(a .)) iv(z) <(options)>
```

Based on the preceding discussion, we obtained the GMM results presented in Table 7, using the following code in STATA (Version 9):

```
xi: xtabond2 roa l.roa l2.roa logbsize indep ceo_chair logmve mtb retstd logsegments
logage debt i.year, gmm(roa logbsize indep ceo_chair logmve mtb retstd
logsegments debt, lag(3 4) collapse) iv(i.year logage) twostep robust small
```

The STATA command incorporates our assumption that only firm age and the year dummies are exogenous. Since our data is sampled every two years, "`lag(3 4)`" invokes instruments from $t-6$ and $t-8$ respectively. We use the "`collapse`" to avoid instrument proliferation and obtain the instrument set specified in equations (28) and (33).

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Table 1: **Prior empirical analysis of the relationship between board structure and firm performance**

Paper	Sample	Period	Performance Measure	Methodology	Relationship
Panel A: Papers examining relationship between board independence and firm performance					
Hermalin and Weisbach (1991)	134	1971-1983	Q, ROA	OLS, 2SLS (Instruments: lagged value of management ownership)	None
Mehran (1995)	153	1979-1980	Q, ROA	OLS	None
Agrawal and Knoeber (1996)	800	1988	Q	2SLS (Instruments: Assets, regulatory dummy, founder dummy)	Negative
Yermack (1996)	452	1984-1991	Q, ROA	OLS, FE	OLS: Negative FE: Positive
Klein (1998)	486	1992-1993	ROA, Jensen productivity measure, Market Returns	OLS	Negative
Bhagat and Black (2002)	934	1988-1991	Q, ROA, ROS, Market Returns	OLS, 2SLS	Negative
Coles, Daniel and Naveen (2007)	8,165	1992-2001	Q	OLS, 3SLS	Negative for high R&D firms
Panel B: Papers examining relationship between board size and firm performance					
Yermack (1996)	452	1984-1991	Q, ROA	OLS, FE	OLS: Negative FE: Negative
Eisenberg, Sundgren and Wells (1998)	879	1992-1994	ROA	2SLS (Instruments: firm age, membership in group)	Negative
Bhagat and Black (2002)	934	1988-1991	Q, ROA, ROS, Market Returns	OLS, 2SLS	Negative (None in some specifications)
Coles, Daniel and Naveen (2007)	8,165	1992-2001	Q	OLS, 3SLS	Positive for large diversified firms

Table 2: **Measuring the bias when explanatory variables is endogenous: Simulation results**

In this table, we report the simulation results from estimating a model with OLS, fixed-effects (FE) and GMM when the explanatory variable is dynamically endogenous and correlated with unobservable effects. The model estimated is: $y_{it} = \mathbf{x}_{it}\beta + \mathbf{z}_{it}\gamma + \eta_i + \nu_{it}$. The true data generating process (DGP) for z_{it} is $z_{it} = \kappa z_{it-1} + \xi_{it}$; and that for x_{it} is $x_{it} = \alpha x_{it-1} + \pi z_{it} + \lambda y_{it-1} + \delta\eta_i + \varepsilon_{it}$. Thus, x_{it} is endogenously related to y_{it-1} through the parameter λ and is endogenously related to the unobserved heterogeneity, η. The parameters used for generating the data in Panels A and B are : $\beta = 0$; $\gamma = 0.6$, $\kappa = 0.9$, $\alpha = 0.7$, $\pi = 0.2$, $\delta = 0.5$. In Panel B, we set $\beta = 0.3$

Panel A: $\beta = 0$, $N = 500$, $T = 5$

	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
	$\lambda = -0.8$			$\lambda = 0.8$			$\lambda = 0.5$		
$\hat{\beta} - \beta$	-0.0993	0.1467	0.0054	0.1018	−0.0559	−0.0001	0.1461	−0.0706	0.0001
	(0.0132)	(0.0160)	(0.0395)	(0.0052)	(0.0102)	(0.0220)	(0.0077)	(0.0139)	(0.0305)
$\hat{\gamma} - \gamma$	−0.0581	−0.0128	−0.0045	−0.1670	0.0230	−0.0010	−0.1776	0.0243	0.0008
	(0.0108)	(0.0108)	(0.0525)	(0.0110)	(0.0115)	(0.0484)	(0.0114)	(0.0111)	(0.0457)
	$\lambda = -0.1$			$\lambda = 0.1$			$\lambda = 0.0$		
$\hat{\beta} - \beta$	0.6335	0.3787	0.0228	0.3222	−0.0739	0.0007	0.4370	−0.0008	0.0066
	(0.0189)	(0.0740)	(0.1433)	(0.0125)	(0.0319)	(0.0691)	(0.0153)	(0.0464)	(0.0990)
$\hat{\gamma} - \gamma$	−0.2440	−0.0857	−0.0010	−0.2134	0.0197	−0.0010	−0.2287	0.0003	0.0020
	(0.0089)	(0.0194)	(0.0419)	(0.0100)	(0.0133)	(0.0446)	(0.0096)	(0.0153)	(0.0431)

Panel B: $\beta = 0.3$, $N = 500$, $T = 5$

	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
	$\lambda = -0.8$			$\lambda = 0.8$			$\lambda = 0.5$		
$\hat{\beta} - \beta$	-0.1001	0.1483	0.0066	0.1018	−0.0563	0.0009	0.1464	−0.0714	0.0004
	(0.0130)	(0.0159)	(0.0330)	(0.0053)	(0.0092)	(0.0361)	(0.0073)	(0.0135)	(0.0427)
$\hat{\gamma} - \gamma$	−0.0589	−0.0127	−0.0050	−0.1662	0.0227	0.0006	−0.1786	0.0243	0.0028
	(0.0105)	(0.0106)	(0.0530)	(0.0109)	(0.0109)	(0.0459)	(0.0109)	(0.0116)	(0.0462)
	$\lambda = -0.1$			$\lambda = 0.1$			$\lambda = 0.0$		
$\hat{\beta} - \beta$	0.6331	0.3781	0.0267	0.3222	−0.0735	0.0028	0.4369	0.0008	0.0128
	(0.0189)	(0.0716)	(0.1560)	(0.0126)	(0.0322)	(0.0776)	(0.0153)	(0.0463)	(0.0955)
$\hat{\gamma} - \gamma$	−0.2439	−0.0859	−0.0024	−0.2134	0.0197	−0.0009	−0.2287	0.0000	0.0008
	(0.0088)	(0.0190)	(0.0422)	(0.0100)	(0.0132)	(0.0439)	(0.0153)	(0.0463)	(0.0955)

Notes

1. All estimated biases and standard errors are based on 1,000 replications. Standard errors of biases are in parentheses.
2. GMM estimation is carried out using the Arellano and Bond (1991) estimation procedure. Instruments used are: $y_{t-2}, y_{t-3}, \ldots, y_1, x_{t-1}, x_{t-2}, \ldots, x_1, z_{t-1}, z_{t-2}, \ldots, z_1$

Table 3: **Summary statistics of board and control variables**

The table contains the sample characteristics of the board and firm characteristics of the firms used in the study. The board variables data comes from the DISCLOSURE database. The control variables data comes from CRSP and COMPUSTAT. **Board size** is the total number of directors on the board. **CEO_Chair** is 1 if the CEO is also the chairman of the board, 0 otherwise. **Board Independence** is the percentage of directors who are not employees of the firm. **Firm Size** is the market value of equity. **Segments** is the number of business segments the firm operates in, as reported by COMPUSTAT. **Firm Age** is computed based on the year the firm first appears on CRSP. **Debt** is the ratio of long-term debt to total assets. **RETSTD** is the standard deviation of the firm's stock returns in the previous twelve months. **Market-to-book** is obtained as the value of equity *plus* book value of assets *minus* book value of equity *minus* deferred taxes, all *divided* by book value of assets. Median values are shown in parentheses; standard deviations are shown in brackets

Panel A: Mean (Median) [Standard Deviation] of Board Variables							
	1991	1993	1995	1997	1999	2001	2003
Board Size	7.79	7.59	7.39	7.49	7.37	7.59	7.93
	(7.00)	(7.00)	(7.00)	(7.00)	(7.00)	(7.00)	(8.00)
	[2.94]	[2.77]	[2.66]	[2.63]	[2.43]	[2.34]	[2.30]
CEO_Chair	0.59	0.60	0.59	0.59	0.59	0.59	0.56
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	[0.49]	[0.49]	[0.49]	[0.49]	[0.49]	[0.49]	[0.49]
Board Independence	0.63	0.64	0.64	0.67	0.67	0.67	0.71
	(0.66)	(0.67)	(0.66)	(0.70)	(0.69)	(0.70)	(0.71)
	[0.18]	[0.18]	[0.19]	[0.18]	[0.17]	[0.15]	[0.14]

Panel B: Mean (Median) [Standard Deviation] of Firm Characteristics							
	1991	1993	1995	1997	1999	2001	2003
Firm Size (millions)	$1,250	$1,240	$1,430	$2,060	$3,130	$2,610	$3,000
	(100)	(114)	(131)	(186)	(186)	(264)	(358)
	[5,380]	[5,150]	[6,770]	[10,040]	[21,200]	[16,000]	[15,700]
Segments	1.60	1.53	1.46	1.49	2.36	2.50	2.35
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	[1.09]	[1.03]	[0.95]	[1.13]	[1.84]	[1.99]	[1.79]
Firm Age	15.04	14.42	13.53	13.42	13.38	14.18	15.95
	(10.00)	(10.00)	(9.00)	(8.00)	(8.00)	(9.00)	(10.00)
	[14.46]	[14.36]	[14.52]	[14.66]	[14.18]	[14.47]	[14.61]
Debt	0.17	0.15	0.16	0.16	0.17	0.16	0.15
	(0.12)	(0.10)	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)
	[0.16]	[0.15]	[0.16]	[0.16]	[0.17]	[0.21]	[0.15]
RETSTD	14.29%	14.62%	12.13%	14.30%	17.87%	21.62%	17.64%
	(12.68)	(12.36)	(10.77)	(12.48)	(15.48)	(18.41)	(15.13)
	[7.96]	[9.99]	[6.84]	[8.74]	[11.79]	[13.37]	[10.93]
Market-to-Book	1.92	2.07	1.93	2.11	2.49	1.94	2.15
	(1.24)	(1.49)	(1.50)	(1.58)	(1.32)	(1.38)	(1.63)
	[2.88]	[1.93]	[2.14]	[1.77]	[4.19]	[1.88]	[1.73]
Number of observations	2,492	2,913	3,025	3,261	3,160	2,754	2,398

Table 4: **How many lags of firm performance are significant?**

In this table, we report results from the OLS estimation of the model:

$$y_{it} = \ {}_1 + \sum_{p=2}^{p=8} \ {}_p y_{it-p} + \ \mathbf{Z}_{it} + \ {}_i + \ {}_{it}; \qquad t = 1999; 2001; 2003$$

y_{it} is ROA or ROS. $\mathbf{Z}_{it}$ includes firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), firm age ($LogAGE$) and leverage ($DEBT$). t-statistics are reported in parentheses. All t-statistics are based on robust, firm-clustered standard errors. $a; b; c$ represent significance at the one percent, five percent and ten percent level respectively. Year dummies are included in all specifications.

Dependent Variable	Performance ROA	Performance ROA	Performance ROS	Performance ROS
Performance$(t-2)$	**0.4823**^{a}		**0.5905**^{a}	
	(16.34)		(10.68)	
Performance$(t-4)$	**0.0766**^{b}		0.0183	
	(2.27)		(0.36)	
Performance$(t-6)$	0.0255	**0.2450**^{a}	0.0701	**0.2681**^{a}
	(0.72)	(5.97)	(5.58)	(5.58)
Performance$(t-8)$	0.0400	**0.1080**^{a}	0.0566	**0.1470**^{a}
	(1.61)	(3.38)	(1.40)	(3.24)
$LogMVE$	**0.0036**^{a}	**0.0079**^{a}	**0.0045**^{a}	**0.0137**^{a}
	(3.37)	(5.79)	(3.22)	(7.45)
MTB	**0.0120**^{a}	**0.0141**^{a}	**0.0124**^{a}	**0.0126**^{a}
	(5.71)	(5.39)	(6.11)	(4.99)
$RETSTD$	$-$**0.0991**^{a}	$-$**0.1711**^{a}	$-$**0.1109**^{a}	$-$**0.1943**^{a}
	($-$3.42)	($-$5.07)	($-$3.28)	($-$4.63)
$LogSEGMENTS$	0.0024	0.0018	0.0018	$-$0.0021
	(1.10)	(0.62)	(0.67)	($-$0.56)
$LogAGE$	$-$0.0043	$-$**0.0081**^{b}	$-$0.0016	$-$**0.0108**^{b}
	($-$1.35)	($-$2.10)	($-$0.41)	($-$2.20)
$DEBT$	0.0166	0.0019	**0.0311**^{b}	**0.0356**^{b}
	(1.23)	(0.12)	(2.28)	(2.17)
R^2	0.47	0.27	0.51	0.30

Table 5: **Relationship between board structure, firm-specific variables and past performance**
In this table we report the results of OLS regressions of current board size ($LogBSIZE$), independence ($INDEP$) and current firm specific variables, on past performance and historic values of the firm specific variables. Performance is measured by return on assets (ROA). The firm-specific include firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), firm age ($LogAGE$) and leverage ($DEBT$). Panel A reports the results of the regressions in which the dependent variables are current levels. Panel B reports the results of the regression in which the dependent variable is the change from $t-1$ to t. All t-statistics (in parentheses) are based on robust standard errors. Year dummies are included in all specifications. Items in **boldface** are significant at the 10% level or higher.

Panel A: Dependent variable is level at time t

	Indep	LogBsize	LogBsize	LogMVE	MTB	Retstd	LogSeg	Debt
ROA($t-2$)	**−0.0185**	**0.0956**	0.0048	**4.2779**	**−0.7200**	**−0.1637**	**−0.1868**	**−0.1027**
	(−1.76)	(6.02)	(0.30)	(21.73)	(−2.47)	(−18.32)	(−4.35)	(−6.31)
LogMVE ($t-2$)	**0.0085**		**0.0241**		**0.2288**	**−0.0105**	**0.0634**	**0.0208**
	(10.31)		(18.96)		(21.63)	(−16.63)	(17.98)	(16.02)
MTB ($t-2$)	**−0.0017**	**−0.0037**	**−0.0024**	**0.1731**		**0.0051**	**−0.0188**	**−0.0113**
	(−2.26)	(1.14)	(−5.46)	(4.17)		(5.21)	(−3.75)	(−3.73)
Retstd ($t-2$)	0.0230	**−0.0533**	**−0.0827**	**−3.1313**	**2.2846**		**−0.2483**	**−0.0876**
	(1.83)	(−4.23)	(−2.73)	(−10.07)	(6.89)		(−3.56)	(−4.29)
LogSeg ($t-2$)	**0.0060**	**0.0010**	0.0067	**0.5535**	**−0.2642**	**−0.0029**		**0.0228**
	(2.97)	(3.03)	(0.32)	(16.83)	(−10.61)	(−1.89)		(6.58)
LogAge ($t-2$)	0.0006	**0.0101**	**0.0082**	**0.3079**	**−0.1773**	**−0.0151**	**0.1225**	**−0.0109**
	(0.55)	(5.53)	(4.61)	(16.00)	(−10.12)	(−17.44)	(22.63)	(−5.66)
Debt ($t-2$)	**−0.0190**	**0.0482**	0.0083	**2.1498**	**−2.0266**	**−0.0118**	**0.1592**	
	(−2.61)	(4.54)	(0.81)	(15.11)	(−16.46)	(−2.03)	(4.46)	
Indep ($t-2$)	**0.6010**	0.0036	− **0.0301**					
	(65.13)	(0.29)	(−2.45)					
LogBsize ($t-2$)	**0.0193**	**0.7836**	**0.7242**					
	(3.94)	(115.34)	(93.38)					
R^2	0.4753	0.7036	0.7147	0.2645	0.0946	0.2657	0.2023	0.0684

Panel B: Dependent variable is change from $t-1$ to t

	ΔIndep	ΔLogBsize	ΔLogBsize	ΔLogMVE	ΔMTB	ΔRetstd	ΔLogSeg	ΔDebt
ROA($t-2$)	−**0.0254**	**0.0158**	0.0067	**0.1667**	−**0.5963**	−**0.1540**	**0.0563**	−**0.0220**
	(−2.40)	(6.13)	(0.42)	(1.88)	(−2.35)	(−17.43)	(1.96)	(−2.20)
LogMVE ($t-2$)	**0.0108**		**0.0244**	−**0.0231**	**0.1082**	−**0.0083**	**0.0167**	**0.0040**
	(14.38)		(20.78)	(−5.65)	(4.03)	(−13.93)	(8.06)	(6.45)
MTB ($t-2$)	−**0.0022**	0.0034	−**0.0024**	−**0.0323**	−**0.7290**	**0.0036**	−**0.0044**	−0.0005
	(−2.65)	(1.36)	(−5.17)	(−5.84)	(10.60)	(5.25)	(−2.81)	(−0.77)
Retstd ($t-2$)	0.0165	−**0.0379**	−**0.1695**	−**0.1358**	**0.9684**	−**0.8251**	−0.0361	−0.0162
	(1.27)	(−3.61)	(−1.96)	(−1.76)	(2.69)	(−46.10)	(−0.68)	(−1.39)
LogSeg ($t-2$)	**0.0057**	**0.0010**	0.0067	−**0.0420**	−**0.1568**	−0.0007	−**1889**	**0.0051**
	(2.71)	(3.17)	(0.32)	(−3.52)	(−4.54)	(−0.49)	(−28.28)	(2.49)
LogAge ($t-2$)	0.0011	**0.0099**	**0.0076**	**0.0149**	−**0.0667**	−**0.0111**	**0.0141**	−**0.0057**
	(0.30)	(4.34)	(4.19)	(2.10)	(−2.77)	(−12.63)	(3.87)	(−4.77)
Debt ($t-2$)	−**0.0129**	**0.0358**	**0.0008**	−**0.1647**	**0.0132**	−**0.0235**	−0.0174	−**0.2644**
	(−1.67)	(3.24)	(0.07)	(−3.83)	(2.54)	(−3.79)	(−0.83)	−(20.60)
Indep ($t-2$)	−**0.4008**							
	(−44.27)							
LogBsize ($t-2$)		−**0.2265**	−**0.2905**					
		(−31.45)	(−35.40)					
R^2	0.2251	0.1823	0.1623	0.0586	0.5375	0.4791	0.2004	0.0684

Table 6: **Does board structure adjust to past performance? Tests of strict exogeneity**

In this table, we report results from the fixed-effects estimation of the model:

$$\mathbf{y}_{i,t} = \quad + \quad \mathbf{X}_{i,t} + \Omega\mathbf{W}_{i,t+2} + \quad _i + \quad _{it}; \qquad t = 1991; 1993; 1995 ::: 2001$$

where $\mathbf{W}_{it+1}$ is a subset of forward values of the corporate governance and control variables, $\mathbf{X}$. $\mathbf{y}$ is firm performance (*ROA*). $\mathbf{X}$ includes board size (*LogBSIZE*), board independence (*INDEP*), a dummy variable which is 1 if the CEO is the board chair (*CEO_CHAIR*), firm size (*LogMVE*), market-to-book ratio (*MTB*), standard deviation of stock returns (*RETSTD*), number of business segments (*LogSEGMENTS*), firm age (*LogAGE*) and leverage (*DEBT*). $\Omega = 0$ is the null hypothesis of strict exogeneity. All *t*-statistics (in parentheses) are based on robust standard errors. Year dummies are included in all specifications.

Dependent Variable: *ROA*(*t*)	1	2	3	4	5
LogBSIZE(*t*)	−**0.0267***	−**0.0282***	−**0.0247***	−**0.0234***	−**0.0251***
	(−3.59)	(−3.80)	(−3.29)	(−3.13)	(−3.32)
INDEP(*t*)	0.0082	0.0088	0.0059	0.0055	0.0050
	(0.81)	(0.86)	(0.57)	(0.54)	(0.49)
CEO_CHAIR(*t*)	0.0005	0.0005	−0.0005	−0.0005	−0.0009
	(0.21)	(0.20)	(−0.17)	(−0.16)	(−0.33)
LogMVE(*t*)	**0.0442***	**0.0438***	**0.0441***	**0.0443***	**0.0416***
	(18.13)	(17.98)	(17.87)	(17.99)	(14.74)
MTB(*t*)	0.0008	0.0008	0.0008	0.0009	0.0011
	(0.75)	(0.79)	(0.80)	(0.76)	(0.97)
RETSTD(*t*)	−0.0085	−0.0082	−0.0091	−0.0091	−**0.0371***
	(−0.56)	(−0.55)	(−0.59)	(−0.59)	(−2.24)
LogSEGMENTS(*t*)	−**0.0070***	−**0.0068***	−**0.0066***	−**0.0067***	−0.0042
	(−2.39)	(−2.34)	(−2.27)	(−2.29)	(−1.34)
LogAGE(*t*)	−**0.0083***	−**0.0087***	−**0.0093***	−**0.0089***	−0.0059
	(−2.20)	(−2.21)	(−2.49)	(−2.35)	(−0.33)
DEBT(*t*)	−**0.0869***	−**0.0864***	−**0.0866***	−**0.0869***	−**0.0758***
	(−5.51)	(−5.46)	(−5.44)	(−5.43)	(−4.51)
LogBSIZE(*t* + 2)	−**0.0136***			−**0.0116***	−**0.0150***
	(−2.08)			(−1.72)	(−2.18)
INDEP(*t* + 2)		−0.0030		−0.0023	−0.0027
		(−0.31)		(−0.23)	(−0.26)
CEO_CHAIR(*t* + 2)			**0.0064***	**0.0062***	**0.0055***
			(2.26)	(2.20)	(1.95)
LogMVE(*t* + 2)					**0.0076***
					(2.64)
MTB(*t* + 2)					0.0003
					(0.17)
RETSTD(*t* + 2)					**0.0997***
					(−5.05)
LogSEGMENTS(*t* + 2)					−0.0041
					(−1.43)
LogAGE(*t* + 2)					−0.0060
					(−0.19)
DEBT(*t* + 2)					−**0.0257***
					(−2.19)

* significant at the ten percent level or smaller

Table 7: **The effect of board structure on current firm performance**

In this table, we report results from the estimation of the model:

$$y_{it} = {}_1 + {}_1 y_{it-2} + {}_2 y_{it-4} + \mathbf{X}_{it} + \mathbf{Z}_{it} + \mathbf{D}_{it} + {}_i + {}_{it}; \qquad t = 1997; 1999; 2001; 2003$$

y_{it} is return on assets (ROA) which is defined as operating income divided by assets. $\mathbf{X}_{it}$ includes board size($LogBSIZE$), board independence ($INDEP$) and a dummy variable which is 1 if the CEO is the board chair (CEO_CHAIR). $\mathbf{Z}_{it}$ includes firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), and leverage ($DEBT$). $\mathbf{D}_{it}$ includes firm age ($LogAGE$) and year dummies. t-statistics are reported in parentheses. For the Static models it is assumed that ${}_1 = {}_2 = 0$. All t-statistics are based on robust, firm-clustered standard errors. $a; b; c$ represent significance at the one percent, five percent and ten percent level respectively.

	Static Model		Dynamic Model	
Dependent Variable (ROA)	Pooled OLS	Fixed Effects	Pooled OLS	System GMM
$LogBSIZE$	$-$**0.0262**[a]	$-$**0.0261**[a]	-0.0033	0.0183
	(-5.67)	(-4.32)	(-0.73)	(0.43)
$INDEP$	$-$**0.0266**[a]	**0.0202**[b]	0.0061	-0.0109
	(-3.56)	(2.48)	(0.82)	(-0.14)
CEO_CHAIR	0.0025	0.0003	0.0018	-0.0127
	(1.09)	(0.13)	(0.83)	(-0.55)
$LogMVE$	**0.0234**[a]	**0.0429**[a]	**0.0070**[a]	**0.0160**[a]
	(27.97)	(21.29)	(6.89)	(2.87)
MTB	$-$**0.0025**[a]	0.0014	**0.0070**[a]	$-$**0.0137**[b]
	(-2.91)	(1.34)	(3.36)	(-2.11)
$RETSTD$	$-$**0.2047**[a]	-0.0117	$-$**0.0832**[a]	$-$**0.5207**[c]
	(-11.69)	(-0.94)	(-4.44)	(-1.77)
$LogSEGMENTS$	$-$**0.0087**[a]	$-$**0.0074**[a]	-0.0012	-0.0068
	(-4.47)	(-3.06)	(-0.76)	(-0.75)
$LogAGE$	**0.0056**[a]	0.0008	-0.0003	$-$**0.0295**[a]
	(4.26)	(0.27)	(-0.20)	(-2.63)
$DEBT$	$-$**0.0307**[a]	$-$**0.0625**[a]	-0.0040	-0.0345
	(-3.37)	(-3.99)	(-0.45)	(-0.52)
$ROA(t-2)$			**0.4833**[a]	**0.7590**[a]
			(24.40)	(3.06)
$ROA(t-4)$			**0.1054**[b]	-0.1212
			(6.00)	(-0.22)
R^2	0.27	0.11	0.41	
$AR(1)$ test (p-value)				(0.00)
$AR(2)$ test (p-value)				(0.87)
Hansen test of over-identification (p-value)				(0.41)
Diff-in-Hansen tests of exogeneity (p-value)				(0.23)

Notes

1. $AR(1)$ and $AR(2)$ are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation
2. Hansen test of over-identification is under the null that all instruments are valid
3. Diff-in-Hansen tests of exogeneity is under the null that instruments used for the equations in levels are exogenous
4. The instruments used in the GMM estimation are: differenced equations: y_{it-6}, y_{it-8}, $\mathbf{X}_{it-6}$, $\mathbf{X}_{it-8}$, $\mathbf{Z}_{it-6}$, $\mathbf{Z}_{it-8}$, $\Delta\mathbf{D}_{it}$; level equations: Δy_{it-4}, $\Delta\mathbf{X}_{it-4}$, $\Delta\mathbf{Z}_{it-4}$, $\mathbf{D}_{it}$

Table 8: **First stage regression and Cragg-Donald statistics for System GMM estimates**

In this table, we report the F-statistics and R^2's of OLS first stage regressions of levels and first-differenced variables on lagged differences and lagged levels respectively. The variables are operating income divided by assets (ROA), board size($LogBSIZE$), board independence ($INDEP$), a dummy variable which is 1 if the CEO is the board chair (CEO_CHAIR), includes firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), firm age ($LogAGE$) and leverage ($DEBT$).

Panel A: Dependent Variable (X) is in levels			
	F-statistic	p-value	R^2
$LogBSIZE$	59.14	0.00	0.1605
$INDEP$	19.19	0.00	0.0584
CEO_CHAIR	7.53	0.00	0.0238
$LogMVE$	61.26	0.00	0.1653
MTB	12.34	0.00	0.0384
$RETSTD$	47.59	0.00	0.1334
$LogSEGMENTS$	86.15	0.00	0.2179
$DEBT$	11.54	0.00	0.0360
	Cragg-Donald statistic: 22.60		

Panel B: Dependent Variable (ΔX) is in first-differences			
$\Delta LogBSIZE$	20.26	0.00	0.0402
$\Delta INDEP$	18.44	0.00	0.0368
ΔCEO_CHAIR	19.05	0.00	0.0379
$\Delta LogMVE$	19.11	0.00	0.0380
ΔMTB	21.45	0.00	0.0425
$\Delta RETSTD$	38.43	0.00	0.0737
$\Delta LogSEGMENTS$	97.33	0.00	0.1677
$\Delta DEBT$	25.07	0.00	0.0493
	Cragg-Donald statistic: 4.29		

Notes

1. For the levels variables (X), the dependent variables are: $\Delta LogBSIZE(t-4)$, $\Delta INDEP(t-4)$, $\Delta CEO\_CHAIR(t-4)$, $\Delta LogMVE(t-4)$, $\Delta MTB(t-4)$, $\Delta RETSTD(t-4)$, $\Delta LogSEGMENTS(t-4)$, $\Delta DEBT(t-4)$, $\Delta ROA(t-4)$, $LogAGE$ and year dummies.
2. For the first-differenced variables (ΔX), the dependent variables are: $LogBSIZE(t-6)$, $INDEP(t-6)$, $CEO\_CHAIR(t-6)$, $LogMVE(t-6)$, $MTB(t-6)$, $RETSTD(t-6)$, $LogSEGMENTS(t-6)$, $DEBT(t-6)$, $LogAGE(t-6)$, $ROA(t-6)$, $LogAGE$ and year dummies.

Table 9: **The effect of board structure on current firm performance: Alternative performance measures**
In this table, we report results from the estimation of the model:

$$y_{it} = {}_1 + {}_1 y_{it-2} + {}_2 y_{it-4} + \mathbf{X}_{it} + \mathbf{Z}_{it} + \mathbf{D}_{it} + {}_i + {}_{it}; \qquad t = 1997; 1999; 2001; 2003$$

y_{it} is either return on sales (ROS) or Tobins Q. $\mathbf{X}_{it}$ includes board size($LogBSIZE$), board independence ($INDEP$) and a dummy variable which is 1 if the CEO is the board chair (CEO_CHAIR). $\mathbf{Z}_{it}$ includes firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), and leverage ($DEBT$). $\mathbf{D}_{it}$ includes firm age ($LogAGE$) and year dummies. t-statistics are reported in parentheses. For the Static models it is assumed that ${}_1 = {}_2 = 0$. All t-statistics are based on robust, firm-clustered standard errors. $a; b; c$ represent significance at the one percent, five percent and ten percent level respectively.

Dependent Variable	Return on Sales (ROS)		Tobin's Q (Industry-adjusted)	
	Static fixed-effects	Dynamic System GMM	Static fixed-effects	Dynamic System GMM
$LogBSIZE$	$-$**0.0319**^{a}	0.0412	$-$**0.6750**^{a}	-0.1618
	(-4.22)	(0.89)	(-6.72)	(-0.31)
$INDEP$	**0.0189**^{c}	-0.0043	**0.2910**^{c}	0.1703
	(1.80)	(-0.05)	(1.83)	(1.34)
CEO_CHAIR	0.0044	-0.0029	-0.1135	-0.2678
	(1.40)	(-0.12)	(-1.59)	(-0.91)
$LogMVE$	**0.0459**^{a}	**0.0248**^{a}	**1.0540**^{a}	0.0223
	(17.20)	(3.25)	(14.81)	(0.21)
MTB	**0.0023**^{b}	-0.0055		
	(1.99)	(-0.42)		
$RETSTD$	$-$**0.0520**^{a}	-0.4234	-0.5213	-3.6937
	(-3.21)	(-1.46)	(1.46)	(-1.28)
$LogSEGMENTS$	$-$**0.0104**^{a}	-0.0070	$-$**0.2133**^{a}	-0.1625
	(-3.19)	(-0.68)	(-4.52)	(-1.57)
$LogAGE$	**0.0073**^{c}	$-$**0.0363**^{a}	$-$**0.4581**^{a}	-0.1436
	(1.91)	(-2.97)	(-7.68)	(-1.18)
$DEBT$	-0.0118	0.0568	$-$**1.513**^{a}	-0.9635
	(-0.89)	(0.81)	(-7.46)	(-1.32)
$ROA(t)$			**0.6775**^{c}	2.3188
			(1.89)	(1.26)
$ROS(t-2)$		**0.4590**^{b}		
		(2.25)		
$ROS(t-4)$		-0.0768		
		(-0.89)		
$Q(t-2)$				**0.4291**^{a}
				(3.14)
$Q(t-4)$				0.0541
				(1.19)
R^2	0.08		0.15	
$AR(1)$ test (p-value)		(0.00)		(0.00)
$AR(2)$ test (p-value)		(0.64)		(0.28)
Hansen test of over-identification (p-value)		(0.30)		(0.68)
Diff-in-Hansen tests of exogeneity (p-value)		(0.17)		(0.44)

Notes
1. $AR(1)$ and $AR(2)$ are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation
2. Hansen test of over-identification is under the null that all instruments are valid
3. Diff-in-Hansen tests of exogeneity is under the null that instruments used for the equations in levels are exogenous
4. The instruments used in the GMM estimation are: differenced equations: y_{it-6}, y_{it-8}, $\mathbf{X}_{it-6}$, $\mathbf{X}_{it-8}$, $\mathbf{Z}_{it-6}$, $\mathbf{Z}_{it-8}$, $\Delta\mathbf{D}_{it}$; level equations: Δy_{it-4}, $\Delta\mathbf{X}_{it-4}$, $\Delta\mathbf{Z}_{it-4}$, $\mathbf{D}_{it}$

Table 10: **The determinants of board structure**

In this table, we report the results from OLS and dynamic GMM regression of board size and board independence on firm size ($LogMVE$), market-to-book ratio (MTB), standard deviation of stock returns ($RETSTD$), number of business segments ($LogSEGMENTS$), firm age ($LogAGE$), leverage ($DEBT$) and (ROA) which is defined as operating income divided by assets. t-statistics are reported in parentheses. The GMM models inludes two lags of the dependent