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Corporate Governance, Product Market Competition, and Equity Prices

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ABSTRACT

This paper examines whether firms in noncompetitive industries benefit more from good governance than do firms in competitive industries. We find that weak governance firms have lower equity returns, worse operating performance, and lower firm value, but only in noncompetitive industries. When exploring the causes of the inefficiency, we find that weak governance firms have lower labor productivity and higher input costs, and make more value-destroying acquisitions, but, again, only in noncompetitive industries. We also find that weak governance firms in noncompetitive industries are more likely to be targeted by activist hedge funds, suggesting that investors take actions to mitigate the inefficiency.

ECONOMISTS OFTEN ARGUE THAT managers of firms in competitive industries have strong incentives to reduce slack and maximize profits, or else the firm will go out of business.[1] Accordingly, the need to provide managers with incentives through good governance—and thus the benefits of good governance—should be smaller for firms in competitive industries. In contrast, firms in noncompetitive industries, where lack of competitive pressure fails to enforce discipline on managers, should benefit relatively more from good governance.

That firms with good governance have better performance *on average* is well established. In a seminal article, Gompers, Ishii, and Metrick (2003, GIM) find that a hedge portfolio that is long in good governance firms ("Democracy firms") and short in weak governance firms ("Dictatorship firms") earns a monthly alpha of 0.71%. Governance is measured using the G-index, which consists of 24 antitakeover and shareholder rights provisions. In addition to showing that good governance is associated with higher equity returns, GIM also show that it is associated with both higher firm value and better operating performance.[2]

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[1] Fritz Machlup's (1967) presidential address to the American Economic Association contains an extensive discussion of this argument. More recent (theory) literature is discussed in Section I.

[2] The evidence is not causal, though GIM examine alternative hypotheses and find no evidence that their results are driven by either reverse causality or an omitted variable bias. That said, other papers show that governance has a causal effect on firm performance using exogenous variation in

The evidence presented in this paper supports the hypothesis that firms in noncompetitive industries benefit more from good governance than do firms in competitive industries. When competition is measured using the Herfindahl–Hirschman index (HHI), we find that the alpha earned by the Democracy–Dictatorship hedge portfolio is small and insignificant in the lowest HHI tercile, is monotonically increasing across HHI terciles, and is large and significant in the highest HHI tercile. This pattern is robust across many specifications—it holds for different governance measures, different competition measures, different asset pricing models, and different sample periods. The latter robustness check is particularly interesting, as prior research shows that GIM's results all but disappear if the sample period is extended beyond 1999 (e.g., Core, Guay, and Rusticus (2006)). If we extend the sample period to 2006, we also find that the *average* alpha across all firms is small and insignificant. However, the alpha in the highest HHI tercile remains large and significant.

There are two potential explanations for the positive alpha earned by the Democracy–Dictatorship hedge portfolio. One is that it may be driven by an omitted variable bias. Such a bias could arise if the G-index is correlated with risk characteristics that are priced during the sample period but that are not captured by the underlying asset pricing model. We address this issue in two ways. First, we extend the four-factor model to include additional risk factors that have been proposed in the literature. Second, we follow GIM and estimate Fama–MacBeth return regressions that include a broad array of control variables. Our results are robust in either case.

The other explanation is that weak governance gives rise to agency costs whose magnitude is underestimated by investors. To test this hypothesis, Core et al. (2006) examine whether analysts correctly predict that weak governance firms have lower earnings than do good governance firms. The authors find that the forecast error (difference between actual and forecasted earnings) is small and insignificant, which leads them to conclude that analysts are not surprised. Consistent with this result, we also find that the *average* forecast error is small and insignificant. However, the forecast error in the highest HHI tercile is large and significant. Thus, analysts underestimate the effect of governance on earnings in precisely those industries in which governance matters for earnings, namely, noncompetitive industries. Whether the forecast error is large enough to fully explain the abnormal return to the Democracy–Dictatorship hedge portfolio remains an open question. At a minimum, it provides evidence in support of the hypothesis that investors are surprised and, consequently, that the abnormal return may not be driven by an omitted variable bias.

We obtain similar results when considering either firm value (Tobin's Q) or operating performance (return on assets (ROA), net profit margin, sales growth, return on equity (ROE)). The relationship between governance and either firm value or operating performance is always small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant

governance in the form of state antitakeover laws (e.g., Bertrand and Mullainathan (2003), Giroud and Mueller (2010)).

in the highest HHI tercile. Our operating performance results are consistent with results in Giroud and Mueller (2010). In that paper, we find that firms in noncompetitive industries experience a significant drop in operating performance after the passage of state antitakeover laws, while firms in competitive industries experience no significant effect. Unlike the present paper, however, the other paper does not consider firm-level governance instruments, nor does it consider long-horizon equity returns or firm value.

Overall, our results suggest that, absent competitive pressure from the product market, weak governance gives rise to agency costs. To gain a better understanding of the nature of these agency costs, we explore in more detail the relationship between (i) governance and investment activity and (ii) governance and productive efficiency. With respect to the former relationship, we find that weak governance firms have higher capital expenditures and make more acquisitions than do good governance firms. This relationship is again small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile.

That weak governance firms make more acquisitions does not necessarily imply that these firms destroy value. However, in a recent article, Masulis, Wang, and Xie (2007) show that high G-index acquirer firms experience significantly lower cumulative abnormal returns (CARs) than do low G-index acquirer firms. Consistent with this result, we also find that high G-index acquirer firms experience significantly lower CARs *on average*. Importantly, however, we find that this relationship is large and significant only in the highest HHI tercile, while it is otherwise small and insignificant. Thus, weak governance firms make more value-destroying acquisitions, but only in noncompetitive industries. This result is noteworthy for two reasons. First, it is a possible explanation for the pattern across HHI terciles that we consistently find in our firm value and operating performance regressions. Second, because CARs measure *unexpected* changes in stock prices, the result suggests that the market does not fully anticipate the negative valuation effects of weak governance in noncompetitive industries. Consequently, it is also a possible explanation for the pattern across HHI terciles that we consistently find in our regressions of equity returns.

As for the relationship between governance and productive efficiency, we find that weak governance firms have lower labor productivity and higher input costs than do good governance firms. Importantly, this relationship is again small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile. We also find qualitatively similar results when considering wages, though the wage results lack statistical significance.

Overall, our results suggest that weak governance firms have lower equity returns, worse operating performance, and lower firm value, but only in noncompetitive industries. In the final part of our analysis, we examine if investors take actions to mitigate the inefficiency. In particular, we examine if weak governance firms, especially those in noncompetitive industries, are more likely to be targeted by activist hedge funds. Using data on hedge fund activism by Brav et al. (2008), we find that weak governance firms in noncompetitive industries are more likely to be targeted by activist hedge funds than any other type of firm, including weak governance firms in competitive industries and good governance firms in noncompetitive industries.[3] We also find that weak governance firms in noncompetitive industries experience a significant drop in the G-index after being targeted by an activist hedge fund, though this result is based on a relatively small sample.

Several recent papers examine the interaction between governance and competition. Cremers, Nair, and Peyer (2008) find that firms in competitive industries have relatively more takeover defenses, but only if the industry is characterized by long-term customer–supplier relationships (e.g., service and durable goods industries). Kadyrzhanova and Rhodes-Kropf (2010) find that four particular G-index provisions that impose a delay on potential acquirers—classified board, blank check, special meeting, and written consent—interact with competition differently than do the remaining 20 G-index provisions. Their explanation is that delay provisions empower target management with bargaining power, which results in higher takeover premia, thus (partly) offsetting the negative entrenchment effects of these provisions. Finally, Guadalupe and Pérez-González (2010) find that firms in countries with tighter product and input market regulations exhibit greater private benefits of control, as measured by the voting premium between shares with differential voting rights.

The rest of this paper is organized as follows. Section I reviews the theory literature. Section II describes the data and provides summary statistics. Section III examines the relationship between governance and long-horizon equity returns, and Section IV examines the relationship between governance and either firm value or operating performance. Section V explores the underlying agency costs associated with weak governance. Section VI examines the likelihood of being targeted by activist hedge funds. Section VII concludes.

I. Theory Literature

Several theory models analyze the implications of product market competition for managerial slack and the resulting need to provide managers with monetary incentives. If better governance is a substitute for monetary incentives, then the predictions of these models can be tied directly to the results in this paper.

In Hart's (1983) model, product market competition unambiguously reduces managerial slack. By assumption, managers care only about reaching a given profit target. Thus, if input costs fall, managers work less hard. In a competitive product market, however, cost reductions that are common across all firms are accompanied by falling prices. Thus, managers cannot afford to slack off but must instead work hard to fulfill their given profit target. Importantly, in Hart's model, managerial income is independent of competition.[4]

[3] We are grateful to Wei Jiang for providing us with the data.

[4] In Hart's model, managers care only about reaching a given subsistence level of income, $\overline{I}$. Income above this level has no value, while income below it is catastrophic. Thus, as long as managers fulfill their given profit target, income will always be $\overline{I}$. As Scharfstein (1988) shows, if

One possible channel through which competition may affect managerial income is through relative performance evaluation. If productivity shocks are correlated across firms, then an increase in the number of competitors may provide additional information that can be used to mitigate moral hazard (Holmström (1982), Nalebuff and Stiglitz (1983)). However, while firm owners are always better off, the effect on managerial incentives is ambiguous. Depending on the underlying probability distribution, the cost of implementing low effort may be reduced to a greater or lesser degree than the cost of implementing high effort. As a result, it may be optimal to give managers either weaker or stronger monetary incentives.

In Schmidt's (1997) model, an increase in competition increases the probability that a firm with high costs becomes unprofitable and must be liquidated. This induces managers to work hard in order to keep their jobs and avoid the disutility of liquidation ("threat-of-liquidation effect"). Moreover, the increased punishment in the event a manager is not successful makes it cheaper to implement a higher level of effort, making it optimal to give managers stronger monetary incentives. On the other hand, a reduction in profits caused by an increase in competition may lower the value of a cost reduction and thus also the benefit of inducing higher effort ("value-of-a-cost-reduction effect").[5] As a result, it may be optimal to give managers weaker monetary incentives. Thus, the overall effect of competition on monetary incentives is (again) ambiguous.

Raith (2003) analyzes the role of competition for monetary incentives in a model with free entry. When the number of firms is fixed, he finds two opposite effects, which happen to exactly cancel each other. For instance, an increase in competition due to greater product substitutability makes it easier for firms to steal demand from rivals, making it optimal to give managers stronger monetary incentives ("business-stealing effect"). On the other hand, an increase in product substitutability results in lower prices and reduces the value of a cost reduction, making it optimal to give managers weaker monetary incentives. With free entry, the effect of competition is no longer ambiguous. For instance, an increase in product substitutability results in lower profits for any given number of firms, inducing some firms to exit. Each surviving firm produces larger output, making it unambiguously optimal to give managers stronger monetary incentives. However, the result is the opposite if competition increases due to a reduction in entry costs. In this case, new firms enter the market, each firm produces less output, and it becomes optimal to give managers weaker monetary incentives. Thus, for any *given* source of variation in competition, an increase in competition has an unambiguous effect on monetary incentives. However, as Raith (2003, p. 1430) acknowledges, "the relationship between competition and managerial incentives depends on what causes variations in the degree of competition, which poses a challenge to empirical tests."

managerial utility is increasing in income, then Hart's main result that product market competition reduces managerial slack can be reversed.

[5] A similar effect is also present in Hermalin's (1992) model, where it is called "change-in-the-relative-value-of-actions effect."

As this brief overview of the theory literature shows, there are plausible arguments for why monetary incentives may be either weaker or stronger in competitive industries. More generally, substituting better governance for monetary incentives, the need to provide managers with incentives through good governance—and thus the benefits of good governance—may be either weaker (substitutes) or stronger (complements) in competitive industries. Sorting out these competing hypotheses is an empirical question, and the objective of this paper is to examine which, if any, is consistent with the data.

II. Data

A. Sample Selection and Definition of Variables

Our sample consists of all firms in the Investor Responsibility Research Center (IRRC) database that have a match in both CRSP and Compustat. Following GIM, we exclude all firms with dual-class shares. To match firms to industries, we, moreover, require a nonmissing SIC code in Compustat. Over the sample period from 1990 to 2006, this leaves us with 3,241 companies.

Our main measure of corporate governance is the G-index introduced by GIM. The index is constructed by adding one index point for each of the 24 (anti-)governance provisions listed in GIM. Higher index values imply weaker governance. GIM refer to companies with a G-index of 5 or less as Democracies and to companies with a G-index of 14 or higher as Dictatorships. The G-index is obtained from the IRRC database and is available for the years 1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006 during the sample period. For intermediate years, we always use the G-index from the latest available year. In robustness checks, we also use the E-index of Bebchuk, Cohen, and Ferrell (2009) and the Alternative Takeover Index (ATI) of Cremers and Nair (2005, CN). The E-index consists of 6 of the 24 provisions listed in GIM. The ATI index consists of three of these provisions.[6] We construct the E-index and the ATI index using IRRC data. The correlation between all three indices is high. Using all IRRC years, the correlation between the G-index and the E-index is 0.71, the correlation between the G-index and the ATI index is 0.68, and the correlation between the E-index and the ATI index is 0.76.

Our main measure of product market competition is the HHI. The HHI is computed as the sum of squared market shares,

$$HHI_{jt} := \sum_{i=1}^{N_j} s_{ijt}^2,$$

where s_{ijt} is the market share of firm i in industry j in year t. Market shares are computed from Compustat using firms' sales (item #12). When computing

[6] For the E-index, we use a cutoff of $E = 0$ for Democracy firms and $E \geq 4$ for Dictatorship firms. Using a cutoff of $E \geq 4$ ensures that the Dictatorship portfolio contains sufficiently many companies relative to the Democracy portfolio (see Table II in Bebchuk et al. (2009)). For the ATI index, we use a cutoff of ATI = 0 for Democracy firms and ATI $\geq$2 for Dictatorship firms.

the HHI, we use all available Compustat firms, including those with dual-class shares. We exclude firms for which sales are either missing or negative. The HHI is a commonly used measure in the empirical industrial organization literature and is well grounded in theory (see Tirole (1988), pp. 221–223). In robustness checks, we also use the "four-firm concentration ratio," which is the sum of market shares of the four largest firms in an industry. This measure is also common in the empirical industrial organization literature and is routinely used by government agencies.

We classify industries using the 48 industry classification scheme of Fama and French (1997, FF). We assign firms to industries by matching the SIC codes of Compustat to the 48 FF industries using the conversion table in the appendix of FF. In robustness checks, we also use four-digit SIC industries.

As our competition measures are computed from Compustat, they only include publicly traded companies. In robustness checks, we also use competition measures provided by the Census Bureau, which include all public and private companies in the United States. Although these measures are more comprehensive, they have several drawbacks. First, they are only available for manufacturing industries, which means the sample is much smaller. Second, the measures are only computed every 5 years. Because our sample period is from 1990 to 2006, we use data from the 1987, 1992, 1997, and 2002 Censuses. For intermediate years, we always use data from the latest available Census. Third, the measures are not available for the 48 FF industries. In the 1987 and 1992 Censuses, they are only available for four-digit SIC industries. In 1997, the Census Bureau switched from SIC to NAICS codes and has since provided competition measures for various NAICS partitions. In our empirical analysis, we use four-digit SIC codes before 1997 and four-digit NAICS codes after 1997. We obtain similar results if we use five- or six-digit NAICS codes after 1997.

B. Empirical Relation between the G-Index and the HHI

Using all firm-year observations from 1990 to 2006, we find that the correlation between the G-index and the HHI is virtually zero. (The correlation is 0.00 with a p-value of 0.50.) This fact has already been noted by GIM (p. 119), who conclude that "[t]here is no obvious industry concentration among these top firms [in the Democracy and Dictatorship portfolios]." Because the HHI is an industry measure, we can also compute the correlation at the industry level. Here, we find a weakly negative correlation of -0.06 (p-value of 0.08) between the HHI and the mean G-index of an industry, which is similar to what Cremers et al. (2008) find.

The Internet Appendix contains further statistics.[7] First, we divide both the Democracy and the Dictatorship portfolio into quintiles by ranking firms according to their HHIs and then sorting them into HHI quintiles. We find that in any given HHI quintile, the empirical distribution of the HHI in the

[7] The Internet Appendix is available on the *Journal of Finance* website at http://www.afajof.org/supplements.asp.

Democracy and Dictatorship portfolios is virtually identical. For instance, firms in the lowest HHI quintile of the Democracy portfolio have a mean (median) HHI of 0.02 (0.02), as do firms in the lowest HHI quintile of the Dictatorship portfolio. Second, when we divide the full sample (not just Democracy and Dictatorship firms) into HHI quintiles, we find that the mean G-index is similar, and the median G-index is identical, in all five quintiles. Importantly, there is no systematic trend. Effectively, this means that it does not matter if we sort firms first by their G-index and then by their HHI, or the other way around. We obtain similar results if we use the E-index or the ATI index, if we use the HHI provided by the Census Bureau, if we use the original sample period in GIM (1990 to 1999) or the post-GIM period (2000 to 2006), and if we use HHI terciles or quartiles instead of quintiles.

III. Corporate Governance and Equity Returns

A. Hedge Portfolios

Our first set of results concerns trading strategies that are jointly based on corporate governance and competition. Following GIM, we compute abnormal returns using Carhart's (1997) four-factor model. The abnormal return is the intercept α of the regression

$$R_t = \alpha + \beta_1 \times RMRF_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times UMD_t + \varepsilon_t, \quad (1)$$

where R_t is the excess portfolio return in month t, $RMRF_t$ is the return on the market portfolio minus the risk-free rate, SMB_t is the size factor (small minus big), HML_t is the book-to-market factor (high minus low), and UMD_t is the momentum factor (up minus down). We construct portfolio returns using monthly return data from CRSP. The *RMRF*, *SMB*, and *HML* factors are obtained from Kenneth French's website. The *UMD* factor is constructed using the procedure described in Carhart (1997).

GIM construct a hedge portfolio that is long in Democracy firms (G-index of 5 or less) and short in Dictatorship firms (G-index of 14 or higher). To analyze the interaction between corporate governance and competition, we divide both the Democracy and the Dictatorship portfolio into three equal-sized portfolios by ranking firms according to their HHIs and then sorting them into HHI terciles. This yields $2 \times 3 = 6$ portfolios: one Democracy and one Dictatorship portfolio for each HHI tercile.[8] For each HHI tercile, we then construct a Democracy–Dictatorship hedge portfolio analogous to GIM. By construction, this implies that all three hedge portfolios contain the same number of stocks.

Our choice of HHI terciles balances two concerns. If too many HHI groups are formed, the number of stocks in each hedge portfolio may be too small to allow for reliable statistical inference. On the other hand, if too few HHI

[8] Our results are unchanged if we sort firms first by their HHIs and then according to whether they are Democracy or Dictatorship firms. This is not surprising, given that the correlation between the HHI and the G-index at the firm level is virtually zero.

groups are formed, the spread in the HHI across hedge portfolios may not be statistically significant. Using HHI terciles, each hedge portfolio contains on average 75 stocks per month, and the average monthly HHI spread (difference between the mean HHI in the lowest and highest HHI tercile) is 0.101, which is statistically significant at all reasonable levels ($p = 0.000$). An alternative way of sorting stocks into HHI terciles would be to use industry- rather than firm-level HHI cutoffs. This would produce an HHI spread of 0.127 ($p = 0.000$), which is slightly larger. Also, all three hedge portfolios would contain the same number of industries by construction. However, because competitive industries have more firms, the number of stocks in each hedge portfolio would no longer be identical. Although the average number of stocks in the low HHI portfolio would be 114, the average number of stocks in the high HHI portfolio would be only 43. Because smaller portfolios are more volatile, this implies that the abnormal return in the high HHI portfolio would be estimated with more noise, making comparisons across HHI terciles difficult. For this reason, we use firm-level HHI cutoffs throughout.[9]

To facilitate comparison with GIM's original results, we use the same sample period, namely, September 1990 to December 1999 (112 monthly returns). In robustness checks, we extend the sample period to December 2006. We rebalance all portfolios in September 1990, July 1993, July 1995, and February 1998, which are the months after which new IRRC data became available. When extending the sample period, we additionally rebalance in November 1999, January 2002, January 2004, and January 2006. To incorporate new values of the HHI, we, moreover, rebalance all portfolios each July using the HHI computed from sales in the previous year. We obtain similar results if we use the HHI computed from sales 2 years ago, or if we use a moving average of the HHIs over the previous 3 years. We always report the results both for value weighted (VW) and equally weighted (EW) portfolios. To compute the VW return on a portfolio in month t, we weigh each individual stock return with the stock's market capitalization at the end of month $t - 1$.

B. Main Results

We first replicate GIM's original results. For VW portfolios, GIM find that the Democracy–Dictatorship hedge portfolio earns a monthly abnormal return of 0.71% ($t = 2.73$). We obtain a very similar result (0.69%, $t = 2.71$).[10] When we exclude companies with missing SIC codes, our result changes only slightly

[9] The statistics discussed in this paragraph can be found in the Internet Appendix. As we show there, our results are qualitatively similar when using industry-level HHI cutoffs. More precisely, while the alphas are very similar, their statistical significance in the highest HHI tercile is slightly weaker, consistent with the smaller size of the high HHI hedge portfolio. Another way to generate a larger HHI spread would be to use HHI quartiles instead of terciles. The results are again qualitatively similar (see the Internet Appendix).

[10] See the Internet Appendix for details. Although our alpha and factor loadings differ slightly from those in GIM, they are identical to those in Core et al. (2006, p. 682).

Table I

Main Results

This table reports the alphas (α) for time-series regressions of monthly excess returns to a hedge portfolio that is long in Democracy firms and short in Dictatorship firms on an intercept (α), the market factor (*RMRF*), the size factor (*SMB*), the book-to-market factor (*HML*), and the momentum factor (*UMD*). Monthly portfolio returns are either value- or equally weighted. The *RMRF, SMB,* and *HML* factors are obtained from Kenneth French's website. The *UMD* factor is computed using the procedure described in Carhart (1997). Democracy firms are firms with a G-index of 5 or less, and Dictatorship firms are firms with a G-index of 14 or higher. G-index is the governance index of Gompers, Ishii, and Metrick (2003). HHI is the Herfindahl–Hirschman index, which is computed as the sum of squared market shares in a given industry based on the 48 industry classification scheme of Fama and French (1997, FF). Market shares are computed based on firms' sales (Compustat item #12) using all available Compustat firms. In the column "All Firms," the hedge portfolio is based on the entire sample. In the columns "Lowest HHI Tercile," "Medium HHI Tercile," and "Highest HHI Tercile," separate hedge portfolios are formed for each individual HHI tercile. First, both the Democracy and the Dictatorship portfolio are divided into three equal-sized portfolios by ranking firms according to their HHIs and then sorting them into HHI terciles. For each HHI tercile, a Democracy–Dictatorship hedge portfolio is then formed that is long in the respective Democracy portfolio and short in the respective Dictatorship portfolio. In Panel A, the sample period is from September 1990 to December 1999. In Panel B, the sample period is either from September 1990 to December 2006 (row 1) or from January 2000 to December 2006 (row 2). *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Value-Weighted Democracy–Dictatorship Hedge Portfolios				Equally Weighted Democracy–Dictatorship Hedge Portfolios			
	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile
Panel A: Main Sample Period (1990–1999)								
α	0.66**	0.30	0.64*	1.47***	0.48**	0.28	0.42	0.72**
t-statistic	(2.57)	(0.90)	(1.70)	(3.38)	(2.19)	(0.85)	(1.27)	(2.38)
Panel B: Alternative Sample Periods								
[1] 1990–2006	0.24	0.06	0.09	0.99**	0.29*	0.00	0.12	0.73***
	(1.22)	(0.21)	(0.30)	(2.55)	(1.77)	(0.00)	(0.48)	(3.12)
[2] 2000–2006	−0.21	−0.41	−0.19	0.26	0.20	−0.36	0.08	0.88**
	(0.65)	(0.87)	(0.41)	(0.40)	(0.76)	(0.91)	(0.19)	(2.24)

(0.66%, $t = 2.57$), suggesting that the excluded companies are not systematically different from the rest.[11]

Table I contains our main results. The first column ("All Firms") shows the abnormal return to the Democracy–Dictatorship hedge portfolio based on the entire sample. The next three columns ("Lowest," "Medium," and "Highest HHI Tercile") show the abnormal returns to the hedge portfolios based on individual HHI terciles. In Panel A, the sample period is from 1990 to 1999. As mentioned above, the VW alpha based on the entire sample is 0.66% ($t = 2.57$) during this period. If we form hedge portfolios based on HHI terciles, we obtain a pattern that is typical of practically all results in this paper: the VW alpha is small

[11] The Democracy and Dictatorship portfolios in GIM contain 572 companies. Excluding companies with missing SIC codes leaves us with 564 companies.

(0.30%) and insignificant in the lowest HHI tercile (competitive industries), is monotonically increasing across HHI terciles, and is large (1.47%) and significant ($t = 3.38$) in the highest HHI tercile. The results for EW portfolios are similar: the EW alpha based on the entire sample is 0.48% ($t = 2.19$), which is similar to what GIM find (0.45%, $t = 2.05$). Moreover, the EW alpha is again small (0.28%) and insignificant in the lowest HHI tercile, is monotonically increasing across HHI terciles, and is large (0.72%) and significant ($t = 2.38$) in the highest HHI tercile.

Overall, our results show that the positive effects of good governance on stock market performance are relatively stronger in noncompetitive industries, which is consistent with the argument that governance and competition are substitutes (see Section I). Our results also show that the relationship between governance and stock market performance is small and insignificant in competitive industries. This latter result has important policy implications, as it suggests that policy efforts to improve governance might benefit from focusing primarily on firms operating in noncompetitive industries. Finally, we would like to caution that even the most competitive industries in our sample are not *perfectly* competitive. Therefore, when we occasionally refer to "competitive industries," we do not mean "perfectly competitive industries." Likewise, when we refer to "noncompetitive industries," we do not mean that these industries are monopolistic. Rather, we understand these terms in a relative sense, as in "more competitive industries" and "less competitive industries" within our sample.

Panel B considers alternative sample periods. In row 1, we extend the sample period to December 2006. Core et al. (2006) find that the VW alpha drops to 0.40% ($t = 1.68$) if the sample period is extended to December 2004. Similarly, we find that the VW alpha drops to 0.24% ($t = 1.22$) and the EW alpha drops to 0.29% ($t = 1.77$) if the sample period is extended to December 2006. Note that this does not necessarily imply that governance does not matter for equity returns. After all, it could be the case that the average alpha is small and insignificant, while the alpha in noncompetitive industries is large and significant. This is precisely what we find: the VW alpha is small (0.06%) and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large (0.99%) and significant ($t = 2.55$) in the highest HHI tercile. The results are similar for EW portfolios.

In row 2, we focus exclusively on the post-GIM period after 1999. Core et al. (2006) find a negative (−0.13%) and insignificant VW alpha for the period from January 2000 to December 2004. Similarly, we find a negative VW alpha of −0.21% and a positive EW alpha of 0.20% for the period from January 2000 to December 2006. Both alphas are insignificant. However, if we form hedge portfolios based on HHI terciles, we obtain a similar pattern as before, though only the EW alpha is significant in the highest HHI tercile (0.88%, $t = 2.24$). This latter finding deserves closer investigation. It could be the case that the insignificant VW alpha in the highest HHI tercile is due to a few bad years for larger firms. Alternatively, it could be the case that the significant EW alpha in the highest HHI tercile is due to a few lucky years for smaller firms.

Table II

Robustness

This table reports the alphas for variants of the regressions in Panel A of Table I. Row 1 restates the results from Panel A of Table I, which are based on HHIs using all Compustat firms in a given 48 FF industry. In row 2, the HHI is replaced with the four-firm concentration ratio, which is the sum of market shares of the four largest firms in an industry. In rows 3 and 4, the competition measures from rows 1 and 2 are replaced with corresponding measures provided by the U.S. Bureau of the Census, where industries are classified using four-digit SIC codes until 1997 and four-digit NAICS codes thereafter. The sample is restricted to manufacturing industries. In row 5, the G-index is replaced with the E-index of Bebchuk, Cohen, and Ferrell (2005). In row 6, the G-index is replaced with the ATI index of Cremers and Nair (2005). In rows 7 and 8, the sample is restricted to firms with above- and below-median institutional ownership, respectively, where institutional ownership is the percentage of shares held by the 18 largest public pension funds as described in Cremers and Nair (2005). In row 9, "new economy" firms as classified by Hand (2003) are excluded from the sample. The sample period is from September 1990 to December 1999. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Value-Weighted Democracy–Dictatorship Hedge Portfolios				Equally Weighted Democracy–Dictatorship Hedge Portfolios			
	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile
[1] HHI (Compustat, 48 FF)	0.66**	0.30	0.64*	1.47***	0.48**	0.28	0.42	0.72**
	(2.57)	(0.90)	(1.70)	(3.38)	(2.19)	(0.85)	(1.27)	(2.38)
[2] Top 4 (Compustat, 48 FF)	0.66**	0.15	0.62*	1.35***	0.48**	0.32	0.55	0.56**
	(2.57)	(0.44)	(1.71)	(3.19)	(2.19)	(0.97)	(1.59)	(2.08)
[3] HHI (Census, Manuf. Ind.)	0.93**	0.02	0.69	1.50**	0.51*	0.31	0.44	0.81*
	(2.43)	(0.03)	(1.33)	(2.46)	(1.82)	(0.75)	(1.12)	(1.74)
[4] Top 4 (Census, Manuf. Ind.)	0.91**	0.00	0.60	1.11*	0.51*	0.41	0.36	0.76*
	(2.39)	(0.00)	(1.11)	(1.93)	(1.80)	(0.94)	(0.80)	(1.67)
[5] E-index	0.74***	0.02	0.84***	1.53***	0.47***	0.21	0.53**	0.68***
	(4.09)	(0.09)	(2.92)	(3.42)	(3.01)	(0.89)	(2.10)	(3.10)
[6] ATI index	0.29*	0.06	0.21	0.64**	0.33**	0.13	0.42**	0.44**
	(1.91)	(0.25)	(0.98)	(2.13)	(2.53)	(0.63)	(2.10)	(2.19)
[7] High Inst. ownership	0.77***	0.28	0.86**	1.60***	0.49*	0.02	0.57	0.81**
	(3.02)	(0.84)	(2.06)	(3.36)	(1.84)	(0.04)	(1.41)	(2.05)
[8] Low Inst. ownership	0.35	0.11	0.17	0.93*	0.48	0.28	0.36	0.72
	(0.94)	(0.21)	(0.31)	(1.70)	(1.61)	(0.55)	(0.86)	(1.32)
[9] Excluding "New Economy"	0.43*	0.27	0.41	0.82**	0.43**	0.24	0.35	0.72**
	(1.71)	(0.79)	(1.05)	(2.04)	(2.03)	(0.71)	(1.10)	(2.35)

To investigate this issue, we split the post-GIM period into two subperiods of equal length (January 2000 to June 2003 and July 2003 to December 2006). Our results (not reported) suggest that GIM's hedge portfolio continues to perform well even after 1999. Although the VW alpha in the highest HHI tercile is insignificant in the first subperiod, it is large and significant in the second subperiod (1.44%, $t = 2.44$). Likewise, the EW alpha in the highest HHI tercile is large and significant in both the first (1.12%, $t = 1.67$) and the second (0.93%, $t = 2.03$) subperiod.

C. Robustness

Table II contains robustness checks. For ease of comparison, we restate our main results from Table I in row 1. In rows 2 to 4, we consider alternative measures of product market competition. In row 2, we use the four-firm concentration ratio based on the 48 FF industries. As can be seen, the results are similar to those in row 1. As the competition measures in rows 1 and 2 are computed from Compustat, they only include publicly traded companies. In rows 3 and 4, we therefore use instead the HHI and four-firm concentration ratio, respectively, provided by the Census Bureau. Although these measures include all public and private companies in the United States, they are only available for manufacturing industries, which means we lose about half of our sample. Furthermore, smaller portfolios are more volatile and thus noisier. Hence, we would expect the statistical significance of our results to become weaker, especially in the (smaller) hedge portfolios based on HHI terciles. Indeed, while the results are qualitatively similar, their statistical significance is slightly weaker.

In rows 5 and 6, we consider alternative measures of corporate governance. In row 5, we use the E-index of Bebchuk et al. (2009). The authors argue that the six provisions included in the E-index are the key drivers behind GIM's results. Accordingly, the E-index might be a less noisy proxy of corporate governance. If this is so, we would expect the statistical significance of our results to become stronger. Indeed, while the results remain qualitatively similar, their significance is slightly stronger, especially for EW portfolios. In row 6, we use the ATI index of CN. Although the G- and E-indices are often interpreted as antitakeover indices, the ATI index truly warrants this interpretation. The results are again similar, albeit the alphas are smaller throughout, especially for VW portfolios.

In rows 7 and 8, we revisit CN's result that the Democracy–Dictatorship hedge portfolio earns a significant alpha only when institutional ownership is high. CN use two proxies for institutional ownership: the percentage of shares held by the 18 largest public pension funds (PP) and the percentage of shares held by the firm's largest institutional blockholder. We obtain similar results using either proxy. For brevity, we only report the results based on the PP measure.[12] We first divide both the Democracy and the Dictatorship portfolio into two equal-sized portfolios based on whether PP lies above or below the median. We then divide each portfolio into three equal-sized portfolios by ranking firms according to their HHIs and then sorting them into HHI terciles. This yields $2 \times 2 \times 3 = 12$ portfolios: one Democracy and one Dictatorship portfolio for each PP-HHI group. For each PP-HHI group, we then construct a Democracy–Dictatorship hedge portfolio analogous to GIM. We obtain three main results. First, the alpha based on the entire sample is significant only when institutional ownership is high. Second, both in the entire sample and in each individual HHI tercile (with one exception), the alpha is larger when institutional ownership is high, though the difference is relatively small for EW portfolios. Both findings are consistent with CN's results. Third, for any given level of institutional ownership, the alpha is small and insignificant in the

[12] The list of the 18 largest pension funds can be found in the Appendix of CN. Holdings are reported in March, June, September, and December of each year. To incorporate holdings information into our trading strategies, we rebalance all portfolios in April, July, October, and January using the holdings of the previous quarter.

lowest HHI tercile, is monotonic across HHI terciles, and is large and (almost always) significant in the highest HHI tercile.

In row 9, we exclude "new economy" firms as classified by Hand (2003). Core et al. (2006) argue that GIM's results are partly driven by these firms. Indeed, when we exclude these firms, we find that both the VW alpha and the EW alpha drop to 0.43% . However, if we form hedge portfolios based on HHI terciles, we obtain a similar pattern as before. The alpha is again small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile.

D. Industry Effects

One might be worried that our results are not driven by the interaction between governance and competition, but rather that they might reflect a *direct effect* of competition on equity returns. For instance, if competition had a positive effect on equity returns, and if firms in the highest HHI tercile of the Democracy portfolio had on average lower HHIs than do firms in the highest HHI tercile of the Dictatorship portfolio, then this could potentially explain our results. However, as we have already discussed in Section II.B, this is rather unlikely: in any given HHI group, the empirical distribution of the HHI in the Democracy and the Dictatorship portfolio is virtually identical. Consequently, the Democracy–Dictatorship hedge portfolio in the highest (or any other) HHI tercile is *both long and short in firms with virtually identical HHIs*, implying that, by construction, any direct effect of the HHI on equity returns should "cancel out." (Likewise, in the Fama–MacBeth return regressions in Section E.2 below, we always include the HHI as a control variable to account for any direct effect of competition on equity returns.)

Panel A of Table III addresses this issue in more detail. In a recent article, Hou and Robinson (2006) document that firms operating in concentrated industries earn significantly lower equity returns even after controlling for the usual four risk factors. The authors provide two explanations. First, barriers to entry may insulate firms in concentrated industries from undiversifiable distress risk. Second, firms in concentrated industries may engage in less innovation. To capture this direct effect of competition on equity returns, Hou and Robinson construct a risk factor, the "concentration premium," by running monthly cross-sectional regressions of individual stock returns on the HHI and control variables. The concentration premium is the estimated coefficient on the HHI. In row 2, we include the Hou-Robinson concentration premium as an additional risk factor. For ease of comparison, we restate our main results from Table I in row 1. As is shown, our results remain virtually unchanged, both for VW and EW portfolios. Note that this is not inconsistent with Hou and Robinson's argument that competition has a direct effect on equity returns. Rather, it reflects the fact that the Democracy–Dictatorship hedge portfolios based on HHI terciles already fully account for this direct effect *by construction*.

In rows 3 and 4, we use industry-adjusted stock returns. Following GIM, we compute the median industry return in a given 48 FF industry using all

Table III

Industry Effects

This table reports the alphas for variants of the regressions in Panel A of Table I. Row 1 restates the results from Panel A of Table I. The regressions in rows 2, 4, 6, and 8 are based on a five-factor model that includes, next to the four factors described in Table I, the Hou-Robinson (2006) concentration premium as an additional risk factor. The regressions in rows 3, 4, 7, and 8 use industry-adjusted returns, which are computed by subtracting from each stock return the corresponding industry median. Median industry returns are computed using all available firms in the CRSP/Compustat sample in a given industry. In Panel A, industries are based on the 48 FF industries. In Panel B, industries are based on four-digit SIC codes. The sample period is from September 1990 to December 1999. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Value-Weighted Democracy–Dictatorship Hedge Portfolios				Equally Weighted Democracy–Dictatorship Hedge Portfolios			
	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile
Panel A: 48 FF Industries								
[1] 4-factor model	0.66**	0.30	0.64*	1.47***	0.48**	0.28	0.42	0.72**
	(2.57)	(0.90)	(1.70)	(3.38)	(2.19)	(0.85)	(1.27)	(2.38)
[2] 5-factor model	0.66**	0.30	0.64*	1.47***	0.48**	0.28	0.42	0.72**
	(2.60)	(0.91)	(1.69)	(3.45)	(2.18)	(0.85)	(1.27)	(2.39)
[3] 4-factor model with Industry-adjusted returns	0.60**	0.38	0.49	1.15***	0.42**	0.31	0.28	0.67**
	(2.10)	(0.92)	(1.38)	(2.72)	(2.13)	(1.02)	(0.95)	(2.29)
[4] 5-factor model with industry-adjusted returns	0.60**	0.39	0.49	1.15***	0.42**	0.31	0.28	0.67**
	(2.10)	(0.93)	(1.38)	(2.76)	(2.13)	(1.01)	(0.95)	(2.29)
Panel B: Four-Digit SIC Industries								
[5] 4-factor model	0.69***	0.47	0.93**	0.98***	0.48**	0.29	0.57	0.63**
	(2.71)	(1.49)	(2.11)	(2.65)	(2.20)	(0.96)	(1.47)	(2.24)
[6] 5-factor model	0.66**	0.44	0.92**	0.92**	0.46**	0.28	0.54	0.61**
	(2.61)	(1.41)	(2.07)	(2.53)	(2.12)	(0.93)	(1.40)	(2.17)
[7] 4-factor model with industry-adjusted returns	0.65**	0.32	0.61	0.75**	0.47***	0.25	0.58	0.59**
	(2.37)	(0.90)	(1.60)	(2.11)	(2.70)	(0.95)	(1.64)	(2.28)
[8] 5-factor model with industry-adjusted returns	0.63**	0.29	0.62	0.70**	0.47***	0.25	0.57	0.58**
	(2.29)	(0.82)	(1.61)	(1.99)	(2.66)	(0.93)	(1.60)	(2.23)

available firms in the merged CRSP/Compustat sample and subtract it from the individual stock returns. As can be seen, the results are again similar.

In a recent article, Johnson, Moorman, and Sorescu (2009, JMS) argue that GIM's original results become insignificant when industry adjustments are based on three- or four-digit SIC industries instead of the 48 FF industries. In Panel B of Table III, we run the same regressions and use the same methodology as in Panel A, except that we replace the 48 FF industries with four-digit SIC industries throughout. That is, we use four-digit SIC industries for (i) the industry adjustment of returns, (ii) the construction of the HHI-based hedge portfolios, and (iii) the computation of the Hou-Robinson concentration premium. As can be seen, our results remain qualitatively similar, except that the difference between the medium and highest HHI tercile becomes less pronounced.

That our results, but also GIM's original results (column "All Firms"), are robust to using four-digit SIC industries in place of the 48 FF industries may be surprising in light of JMS's recent critique. As our results suggest, the issue is not so much whether industry adjustments are done using the 48 FF industries or some finer industry partitioning. Rather, the issue is that JMS do not include all available firms in their industry benchmark portfolios—that is, all firms that are in the merged CRSP/Compustat sample—but only a small subset, namely, only firms that are in the IRRC sample. During the 1990 to 1999 period, the merged CRSP/Compustat sample includes on average 8,001 firms per year. By contrast, the IRRC sample includes only about 18% of these firms—specifically, 1,429 firms per year—implying that JMS exclude on average more than 80% of the firms in a given industry when computing industry benchmark returns. In fact, JMS do not even utilize the full IRRC sample: when industry-adjusting the returns of Democracy (Dictatorship) firms, they only include non-Democracy (non-Dictatorship) firms in their industry benchmark portfolios.[13]

Excluding more than 80% of the firms in a given industry when computing industry benchmark returns has potentially serious implications. First, as firms without any industry peers must be dropped from the hedge portfolio (because industry benchmark returns cannot be computed), JMS's hedge portfolio is much smaller. Smaller portfolios are more volatile and thus noisier, causing a downward bias in the significance of the alpha. For instance, using four-digit SIC industries, JMS's hedge portfolio contains about 10% fewer stocks than GIM's hedge portfolio. Second, for those firms that are *not* dropped from JMS's hedge portfolio, the industry-adjusted returns are often extremely noisy because the industry benchmark returns are based on only a few firms. Again, this causes a downward bias in the significance of the alpha. For instance, about 15% of the firms in JMS's hedge portfolio have only *one* four-digit SIC industry peer, implying that industry adjustments are done by subtracting the return of a *single* firm. Likewise, about 26% of the firms in JMS's hedge portfolio have three or fewer four-digit SIC industry peers. In contrast, if benchmark returns are computed using all available firms—that is, all firms in a given industry that are in the merged CRSP/Compustat sample—only 1% of the firms in the Democracy–Dictatorship hedge portfolio have one four-digit SIC industry peer, and only 4% of them have three or fewer four-digit SIC industry peers. Third, because less competitive industries have fewer firms to begin with, the resulting bias is systematically related to the competitiveness of the industry: excluding more than 80% of the firms in a given industry may be less problematic in a competitive industry, which may still have sufficiently many remaining firms. However, in a less competitive industry, which has relatively few firms to

[13] Lewellen and Metrick (2010) document similar shortcomings with JMS's methodology. More generally, they review a variety of industry construction methodologies in the context of the GIM sample and explore the many tradeoffs that researchers face when selecting an industry classification standard and industry construction methodology for use in asset pricing tests.

begin with, it may imply that benchmark returns are computed from only a few firms, making the industry-adjusted returns very noisy. To illustrate this point, we have re-estimated our results from rows 7 and 8 in Panel (B), but instead of using all available firms in an industry, we have used JMS's methodology of selecting industry peer firms. While the alpha coefficients in the highest HHI tercile are either identical (for EW portfolios) or even slightly larger (for VW portfolios), their statistical significance becomes much weaker (t-statistics between 1.43 and 1.66), consistent with the fact that JMS's hedge portfolio is much smaller and their industry-adjusted returns are very noisy.

JMS also combine industry- with characteristics-adjusted returns, where all monthly returns, including those in the industry benchmark portfolios, are additionally adjusted by subtracting from each individual stock return the return of the corresponding size, book to market, and momentum portfolio from the 125 portfolios in Daniel et al. (1997) and Wermers (2004). The results are again similar to those in Panel B (see the Internet Appendix).

E. Omitted Variable Bias

An important concern is that the abnormal return to the Democracy–Dictatorship hedge portfolio may be driven by an omitted variable bias. Such a bias could arise if the G-index is correlated with firm or other characteristics that are priced during the sample period but that are not captured by the asset pricing model in equation (1). We address this issue in two ways. First, we consider alternative asset pricing models. Second, we follow GIM and estimate Fama–MacBeth return regressions that include a broad array of control variables.

E.1. Alternative Asset Pricing Models

Table IV considers alternative asset pricing models. In row 1, we use the market model in place of the four-factor model. As is shown, all results are weaker, especially for EW portfolios, where none of the alphas are significant. There is a simple explanation: the Democracy–Dictatorship hedge portfolio not only captures the effects of governance, but it also partly captures the effects of size and book-to-market, which are unequally distributed among Democracy and Dictatorship firms. For example, Table IV in GIM (p. 123) shows that the HML factor has a negative loading among Democracy stocks but a positive loading among Dictatorship stocks. Both loadings are highly significant. In the Democracy–Dictatorship hedge portfolio, the HML factor consequently has a negative and highly significant loading, with the effect that removing this factor will necessarily shift the intercept of the regression (i.e., the alpha) downward. Likewise, the SMB factor has a negative and significant loading among Democracy stocks but a small and insignificant loading among Dictatorship stocks, with the effect that the overall loading in the Democracy–Dictatorship hedge portfolio is negative and highly significant. Again, removing this factor will necessarily shift the intercept of the regression downward.

Table IV

Alternative Asset Pricing Models

This table reports the alphas for variants of the regressions in Panel A of Table I. In row 1, the four-factor model is replaced with the market model. In row 2, the Carhart (1997) momentum factor is replaced with the momentum factor from Kenneth French's website. The regressions in rows 3–7 are based on five-factor models that include, next to the four factors described in Table I, the co-skewness factor of Harvey and Siddique (2007) (row 3), the aggregate volatility factor of Ang et al. (2006) (row 4), the downside risk factor of Ang, Chen, and Xing (2006) (row 5), the liquidity factor of Pástor and Stambaugh (2003) (row 6), and the takeover factor of Cremers, Nair, and John (2009) (row 7), respectively. The sample period in rows 1–6 is from September 1990 to December 1999. The sample period in row 7 is from January 1991 to December 1999. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Value-Weighted Democracy–Dictatorship Hedge Portfolios				Equally Weighted Democracy–Dictatorship Hedge Portfolios			
	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	All Firms	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile
[1] Market model	0.48*	0.17	0.49	1.17**	0.15	−0.03	0.08	0.39
	(1.74)	(0.49)	(1.34)	(2.51)	(0.59)	(0.09)	(0.25)	(1.16)
[2] French's momentum factor	0.47*	0.10	0.61	1.13**	0.23	0.08	0.10	0.53*
	(1.82)	(0.29)	(1.56)	(2.56)	(0.99)	(0.23)	(0.29)	(1.69)
[3] Co-skewness factor	0.65**	0.30	0.65*	1.42***	0.46**	0.26	0.40	0.71**
	(2.52)	(0.89)	(1.74)	(3.33)	(2.12)	(0.78)	(1.23)	(2.33)
[4] Aggregate volatility factor	0.72***	0.27	0.76**	1.59***	0.61***	0.42	0.59*	0.80**
	(2.77)	(0.78)	(2.02)	(3.61)	(2.85)	(1.25)	(1.83)	(2.61)
[5] Downside risk factor	0.69**	0.22	1.07**	1.58***	0.62**	0.43	0.63	0.81**
	(2.08)	(0.51)	(2.22)	(2.81)	(2.19)	(0.99)	(1.55)	(2.10)
[6] Liquidity factor	0.57**	0.26	0.61	1.32***	0.44**	0.28	0.36	0.68**
	(2.31)	(0.77)	(1.62)	(3.15)	(2.02)	(0.83)	(1.10)	(2.23)
[7] Takeover factor	0.31	−0.05	0.23	1.41***	0.18	−0.04	0.07	0.54
	(1.04)	(0.12)	(0.50)	(2.75)	(0.75)	(0.10)	(0.19)	(1.57)

In row 2, we use Kenneth French's instead of Carhart's momentum factor. The two momentum factors are similar, except that French's momentum factor contains an additional sort based on size. As is shown, the results are qualitatively similar but weaker, especially for EW portfolios. In rows 3 to 6, we extend the four-factor model by including additional risk factors that have been proposed in the literature: the co-skewness factor of Harvey and Siddique (2000), the aggregate volatility factor of Ang et al. (2006), the downside risk factor of Ang, Chen, and Xing (2006), and the liquidity factor of Pástor and Stambaugh (2003). We construct these factors following the authors' descriptions, except for the liquidity factor, which we obtain from the WRDS website. As is shown, the results remain similar throughout.

In row 7, we include the takeover factor of Cremers, Nair, and John (2009, CNJ).[14] The takeover factor is constructed by ranking companies based on the likelihood of being a takeover target (from logit regressions) and then taking a long (short) position in the top (bottom) quintile. As the logit regressions use lagged governance data, the first 4 months of the sample period must

[14] We are grateful to Martijn Cremers for providing us with the data.

be dropped. As CNJ point out, it is not obvious what effect the takeover factor might have on GIM's results. Although the G-index and takeover activity are clearly related, many of the provisions in the G-index are unrelated to takeovers. On the other hand, takeovers may occur for reasons unrelated to governance, such as synergies. When CNJ estimate a five-factor model that includes the takeover factor as an additional risk factor, they find that the abnormal return to the Democracy–Dictatorship portfolio becomes insignificant, suggesting that it is primarily driven by G-index provisions that are takeover related. Consistent with this result, we also find that the (average) alpha based on the entire sample becomes insignificant. However, the alpha remains monotonic across HHI terciles and, at least for VW portfolios, significant in the highest HHI tercile, suggesting that the abnormal return to the Democracy–Dictatorship portfolio is at least partly also driven by G-index provisions that are unrelated to takeovers.

E.2. Fama–MacBeth Return Regressions

To address concerns that the abnormal return to the Democracy–Dictatorship hedge portfolio might be driven by an omitted variable bias, GIM estimate Fama–MacBeth return regressions that include a broad array of control variables. We augment GIM's specification in two ways. First, we interact all governance measures with the HHI. Second, we include additional control variables. We estimate the cross-sectional regression

$$r_{it} = \alpha_t + \boldsymbol{\beta}_t'(G_{it} \times \mathbf{I}_{it}) + \boldsymbol{\gamma}_t'\mathbf{X}_{it} + \varepsilon_{it}, \tag{2}$$

where r_{it} is the return on firm i's stock in month t, G_{it} is either the G-index or a Dictatorship dummy, $\mathbf{I}_{it}$ is a (3×1) vector of HHI dummies, and $\mathbf{X}_{it}$ is a vector of control variables. The HHI dummies indicate whether the HHI of firm i in month t lies in the lowest, medium, or highest tercile of its empirical distribution. All right-hand-side variables are lagged. We estimate equation (2) for each month and calculate the mean and time-series standard deviation of the 112 monthly estimates to obtain the Fama–MacBeth coefficients and standard errors.

As elements of $\mathbf{X}$, we include the full set of control variables used in GIM: firm size; book-to-market ratio; stock price; returns from months $t-3$ to $t-2$, from $t-6$ to $t-4$, and from $t-12$ to $t-7$; trading volume of NYSE or Amex stocks; trading volume of NASDAQ stocks; a NASDAQ dummy; an S&P 500 dummy; dividend yield; sales growth over the previous 5 years; and institutional ownership. A description of all these variables can be found in the Appendix of GIM. To control for any direct effect of competition, we also include HHI dummies. Finally, we include a measure of idiosyncratic volatility. In a recent paper, Ferreira and Laux (2007, FL) show that firms with fewer antitakeover provisions exhibit higher levels of idiosyncratic volatility. This could have pricing implications. Our measure of idiosyncratic volatility is the same as in FL.

Table V

Fama-MacBeth Return Regressions

This table reports the Fama-MacBeth coefficients from monthly cross-sectional regressions of individual stock returns on an intercept, either the G-index or a Dictatorship dummy, and control variables. The Dictatorship dummy equals one if a firm is a Dictatorship firm and zero otherwise. The control variables are firm size; book-to-market ratio; stock price; returns from months $t-3$ to $t-2$, from $t-6$ to $t-4$, and from $t-12$ to $t-7$; trading volume of NYSE or Amex stocks; trading volume of NASDAQ stocks; a NASDAQ dummy; an S&P 500 dummy; dividend yield; sales growth over the previous 5 years; institutional ownership; and the Ferreira-Laux (2007) measure of idiosyncratic volatility. A description of all control variables (except for idiosyncratic volatility) can be found in Gompers, Ishii, and Metrick (2003). In columns 2 and 4, the G-index and the Dictatorship dummy are interacted with HHI dummies indicating whether the HHI lies in the lowest, medium, or highest tercile of its empirical distribution, and HHI dummies are included as additional control variables. All right-hand-side variables are lagged. The samples in columns 3 and 4 are restricted to Democracy and Dictatorship firms. The G-index, the HHI, and Democracy and Dictatorship firms are defined in Table I. Columns 1 and 3 report the coefficients on the G-index and the Dictatorship dummy, respectively, and columns 2 and 4 report the coefficients on interaction terms between either the G-index or the Dictatorship dummy and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. The sample period is from September 1990 to December 1999. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	[1]	[2]	[3]	[4]
G-index	−0.04			
	(1.28)			
G-index × HHI (low)		−0.02		
		(0.21)		
G-index × HHI (medium)		−0.02		
		(0.59)		
G-index × HHI (high)		−0.12*		
		(1.93)		
Dictatorship			−0.77**	
			(2.43)	
Dictatorship × HHI (low)				−0.24
				(0.60)
Dictatorship × HHI (medium)				−1.00*
				(1.72)
Dictatorship × HHI (high)				−1.77**
				(2.52)
HHI (medium)		0.01		0.67
		(0.01)		(1.33)
HHI (high)		0.78		0.82
		(0.99)		(1.64)
Number of months	112	112	112	112
Number of observations	122,595	122,595	21,299	21,299

Table V shows the results. In column 1, the coefficient on the noninteracted G-index is small (−0.04) and insignificant, which is identical to the result in GIM. The outcome is markedly different if we restrict the sample to Democracy and Dictatorship firms and use a Dictatorship dummy as our governance proxy. In column 3, the coefficient on the noninteracted Dictatorship dummy is large and significant (−0.77, t = 2.43), which is similar to the result in GIM (0.76, t = 2.38). (GIM use a Democracy dummy instead of a Dictatorship dummy, which implies that the sign of the coefficient is reversed.) As GIM note, this coefficient can be interpreted as a monthly abnormal return. Hence, the monthly abnormal return to Democracy stocks is 0.77% higher than the monthly abnormal return to Dictatorship stocks, which is roughly of similar magnitude as the monthly abnormal return of 0.66% to the Democracy–Dictatorship hedge portfolio shown in Table I. That the results are much stronger if we use a Dictatorship dummy as opposed to the G-index is not surprising: as equity returns are very noisy, the effect can often only be found in the extremes. In columns 2 and 4, we find the same pattern across HHI terciles as before. Regardless of whether we use the G-index or a Dictatorship dummy as our governance proxy, the coefficient is always small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile. Importantly, that the results are similar if we use a broad array of control variables mitigates concerns that they might be driven by an omitted variable bias.

F. Analysts' Earnings Forecasts

There are two potential explanations for the abnormal return to the Democracy–Dictatorship hedge portfolio. One is that the G-index is correlated with risk characteristics that are priced during the sample period but that are not captured by the asset pricing model in equation (1). As is shown in the previous section, and consistent with GIM's own results, we find no support for this hypothesis. The other explanation is that weak governance gives rise to agency costs whose magnitude is underestimated by investors. Consistent with the first part of this hypothesis, GIM find that weak governance is associated with both higher capital expenditures and higher acquisition activity. Likewise, Core et al. (2006, CGR) and GIM both find that weak governance is associated with worse operating performance. However, CGR find no evidence for the second part of the hypothesis, namely, that investors are surprised. The authors test whether the stock market underperformance of weak governance firms is due to investor surprise about the poor operating performance of these firms. Using analysts' earnings forecasts to proxy for investors' expectations, they find no significant relationship between governance proxies and analysts' forecast errors.

Following CGR, we use analysts' earnings forecasts to proxy for investors' expectations. Data on analysts' earnings forecasts are obtained from the Institutional Brokers' Estimate System (I/B/E/S). Our main measure is the mean I/B/E/S consensus forecast of annual earnings per share (EPS) measured 8 months prior to the fiscal year's end. We obtain virtually identical results using median I/B/E/S consensus forecasts. Measuring analysts' forecasts 8 months before the fiscal year's end ensures that the analysts know the previous year's earnings when making their forecasts. To mitigate the effect of outliers, we remove observations for which the forecast error is larger than 10% of the share price in the month of the forecast (less than 3% of the sample) (e.g., Lim (2001), Teoh and Wong (2002)). Also, to ensure that consensus forecasts constitute reliable proxies of market expectations, we require that a company be followed by at least five analysts (e.g., Easterwood and Nutt (1999), Loha and Mianc (2006)).

We estimate the equation

$$y_{it} = \alpha_j + \alpha_t + \boldsymbol{\beta}'(G_{it-1} \times \mathbf{I}_{it-1}) + \boldsymbol{\gamma}'\mathbf{X}_{it-1} + \varepsilon_{it}, \tag{3}$$

where y_{it} is either the mean I/B/E/S consensus forecast of annual EPS, the actual I/B/E/S annual EPS, or the forecast error (difference between actual and forecasted EPS) for firm i in year t, all scaled down by lagged total assets per share, where total assets is the book value of total assets (Compustat item #6), α_j and α_t are industry and year fixed effects, G_{it-1} is a Dictatorship dummy, $\mathbf{I}_{it-1}$ is a (3×1) vector of HHI dummies, and $\mathbf{X}_{it-1}$ is a vector of control variables. All right-hand-side variables are lagged. As control variables, we include HHI dummies, the book-to-market ratio, and firm size. Firm size is the logarithm of the book value of total assets. The book-to-market ratio is computed as the logarithm of the ratio of the book value of equity (item #60 + item #74) divided by the market value of equity (item #199 $\times$ item #25). The sample is restricted to Democracy and Dictatorship firms. The sample period is from 1991 to 1999. Standard errors are clustered at the industry level.[15]

Table VI shows the results. (Robustness checks can be found in the Internet Appendix.) Columns 1 and 2 show that Dictatorship firms exhibit on average lower EPS than Democracy firms and that analysts correctly predict this outcome. The forecast error, which is shown in column 3, is small and insignificant. Based on this evidence, CGR conclude that investors are not surprised. However, columns 4 to 6 paint a more nuanced picture. Column 4 shows that Dictatorship firms exhibit lower EPS only in noncompetitive industries (highest HHI tercile). Remarkably, analysts correctly predict this outcome: in column 5, the difference in *forecasted* EPS between Dictatorship and Democracy firms is significant only in the highest HHI tercile, while it is otherwise small and insignificant. Importantly, however, while analysts correctly predict that governance matters for EPS only in noncompetitive industries, they underestimate the magnitude of this effect: in column 6, the forecast error in the highest HHI tercile is large (-0.43) and significant ($p = 0.07$). *Thus, analysts underestimate the effect of governance on earnings in precisely those industries in which governance matters for earnings, namely, noncompetitive industries.* The economic magnitude of the forecast error is large: in the highest HHI tercile, analysts underestimate the difference in EPS between Dictatorship and Democracy firms

[15] CGR use the Fama–MacBeth method while accounting for serial correlation using the Newey–West procedure with one lag. However, when the dependent and independent variables are both persistent, the Fama–MacBeth method produces biased standard errors even if combined with the Newey–West procedure (Petersen (2009)). To avoid this bias, we estimate a panel regression with fixed effects and clustered standard errors. The choice of industry rather than firm fixed effects is due to insufficient within-variation of the G-index.

Table VI

Analysts' Forecast Errors

This table reports the coefficients from panel regressions of either the actual I/B/E/S annual earnings per share (EPS) (columns 1 and 4), the mean I/B/E/S consensus forecast of annual EPS (columns 2 and 5), or the forecast error (actual I/B/E/S annual EPS minus mean I/B/E/S consensus forecast of annual EPS; columns 3 and 6), all scaled down by lagged total assets per share, on an intercept, year and industry fixed effects, a Dictatorship dummy, the book-to-market ratio, and firm size. Lagged total assets per share is the book value of assets (Compustat item #6) in the previous year divided by the number of shares in the month of the forecast. Firm size is the logarithm of the book value of assets. The book-to-market ratio is computed as the logarithm of the ratio of the book value of equity (item #60 + item #74) divided by the market value of equity (item #199 × item #25). In columns 4–6, the Dictatorship dummy is interacted with HHI dummies, and HHI dummies are included as additional control variables. All right-hand-side variables are lagged. The sample is restricted to Democracy and Dictatorship firms. Democracy and Dictatorship firms are defined in Table I, and the HHI dummies and the Dictatorship dummy are defined in Table V. All coefficients are multiplied by 100. Columns 1–3 report the coefficients on the Dictatorship dummy, and columns 4–6 report the coefficients on interaction terms between the Dictatorship dummy and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. Standard errors are clustered at the industry level. The sample period is from 1991 to 1999. t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Actual [1]	Forecast [2]	Error [3]	Actual [4]	Forecast [5]	Error [6]
Dictatorship	−0.57*	−0.48	−0.09			
	(1.66)	(1.25)	(0.68)			
Dictatorship × HHI (low)				0.23	0.13	0.10
				(0.31)	(0.19)	(0.72)
Dictatorship × HHI (medium)				0.11	0.04	0.07
				(0.21)	(0.08)	(0.31)
Dictatorship × HHI (high)				−2.02***	−1.59**	−0.43*
				(2.71)	(2.16)	(1.81)
HHI (medium)				0.79	0.57	0.22
				(1.14)	(1.12)	(0.59)
HHI (high)				2.30***	0.99*	1.31**
				(2.71)	(1.70)	(2.15)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,071	1,071	1,071	1,071	1,071	1,071
Adj. R^2	0.40	0.43	0.11	0.40	0.43	0.11

by about 21%. Whether this forecast error is large enough to fully explain the abnormal return to the Democracy–Dictatorship hedge portfolio remains an open question. At a minimum, it provides evidence in support of the hypothesis that investors are surprised and, therefore, that the abnormal return may not be driven by an omitted variable bias.

IV. Corporate Governance, Firm Value, and Operating Performance

To provide further evidence, GIM examine the relationship between governance and firm value (Tobin's Q) and governance and operating performance (net profit margin, ROE, sales growth). Core et al. (2006) extend GIM's results by examining the relationship between governance and return on assets (ROA). In this section, we examine whether any of these relationships are different in competitive versus noncompetitive industries.

A. Corporate Governance and Firm Value

To examine the relationship between governance and firm value, we estimate

$$Q^{*}_{it} = \alpha_j + \alpha_t + \boldsymbol{\beta}' (G_{it} \times \mathbf{I}_{it}) + \boldsymbol{\gamma}'\mathbf{X}_{it} + \varepsilon_{it}, \tag{4}$$

where Q^{*}_{it} is the industry-adjusted Tobin's Q of firm i in year t, G_{it} is the G-index, $\mathbf{I}_{it}$ is a (3×1) vector of HHI dummies, α_j and α_t are industry and year fixed effects, and $\mathbf{X}_{it}$ is a vector of control variables. The choice of industry rather than firm fixed effects is due to insufficient within-variation of the G-index, a point that has already been made by GIM (p. 126). Tobin's Q is the market value of assets divided by the book value of assets (Compustat item #6), where the market value of assets is the book value of assets plus the market value of common stock (item #24 $\times$item #25) minus the sum of the book value of common stock (item #60) and balance sheet deferred taxes (item #74). Industry-adjusted Tobin's Q is computed by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. As elements of $\mathbf{X}$, we include the full set of control variables used in GIM: firm size, which is the logarithm of the book value of assets, firm age (in logs), an S&P 500 dummy, and a Delaware dummy. To control for any direct effect of competition on firm value, we also include HHI dummies. Standard errors are clustered at the industry level. The sample period is from 1990 to 2006.

Table VII presents the results.[16] (Robustness checks can be found in the Internet Appendix.) In column 1, the coefficient on the noninteracted G-index is -0.036 ($t = 3.46$), implying that an increase in the G-index by one index point is associated with a 3.6% lower value for Tobin's Q. In column 2, we obtain the same pattern across HHI terciles as before: the coefficient on the G-index is small (-0.005) and insignificant in the lowest HHI tercile, is larger (-0.043) and significant ($t = 1.77$) in the medium HHI tercile, and is largest (-0.065) and significant ($t = 3.17$) in the highest HHI tercile.

B. Corporate Governance and Operating Performance

To examine the relationship between governance and operating performance, we use the same specification as in equation (4), except that the dependent

[16] We obtain similar results if we use median (least absolute deviation) regressions instead of OLS. We also obtain similar results if we estimate year-by-year cross-sectional regressions. For the years 1990 to 2006, the coefficient on the G-index is small and insignificant in the lowest HHI tercile in all years, is monotonic across HHI terciles in most years (12 out of 17 years), and is always large and almost always (16 out of 17 years) significant in the highest HHI tercile (see the Internet Appendix).

Table VII
Tobin's *Q*

This table reports the coefficients from panel regressions of industry-adjusted Tobin's Q on an intercept, year and industry fixed effects, the G-index, firm size, firm age, an S&P 500 dummy, and a Delaware dummy. A description of all control variables can be found in Gompers, Ishii, and Metrick (2003). Tobin's Q is the market value of assets divided by the book value of assets (Compustat item #6), where the market value of assets is the book value of assets plus the market value of common stock (item #24 $\times$ item #25) minus the sum of the book value of common stock (item #60) and balance sheet deferred taxes (item #74). Industry-adjusted Tobin's Q is computed by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. In column 2, the G-index is interacted with HHI dummies, and HHI dummies are included as additional control variables. The G-index is defined in Table I, and the HHI dummies are defined in Table V. Column 1 reports the coefficient on the G-index, and column 2 reports the coefficients on interaction terms between the G-index and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. Standard errors are clustered at the industry level. The sample period is from 1990 to 2006. t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	[1]	[2]
G-index	−0.036***	
	(3.46)	
G-index × HHI (low)		−0.005
		(0.33)
G-index × HHI (medium)		−0.043*
		(1.77)
G-index × HHI (high)		−0.065***
		(3.17)
HHI (medium)		0.463
		(1.42)
HHI (high)		0.671**
		(2.40)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Number of observations	20,051	20,051
Adj. R^2	0.08	0.08

variable is now either ROA, net profit margin (NPM), sales growth, or ROE. ROA is net income (Compustat item #172) divided by the book value of total assets (item #6), NPM is net income divided by sales (item #12), sales growth is the growth in sales over the previous 5 years, and ROE is net income divided by the book value of common stock (item #60). Following GIM, we include the logarithm of the book-to-market ratio in the previous year as an additional control variable. The book-to-market ratio is computed as the ratio of the book value of common stock plus balance sheet deferred taxes (item #74) divided by the market value of common stock (item #24 $\times$ item #25). All dependent variables are industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. To account for outliers, we trim all dependent variables at

Table VIII

Operating Performance

This table reports the coefficients from panel regressions of industry-adjusted measures of operating performance on an intercept, year and industry fixed effects, the G-index, and control variables. The control variables are the same as in Table VII plus the logarithm of the book-to-market ratio in the previous year. The book-to-market ratio is computed as the ratio of the book value of common stock (Compustat item #60) plus balance sheet deferred taxes (item #74) divided by the market value of common stock (item #24 × item #25). In columns 2, 4, 6, and 8, the G-index is interacted with HHI dummies, and HHI dummies are included as additional control variables. The G-index and the HHI dummies are defined in Tables I and V, respectively. All right-hand-side variables are lagged. In columns 1 and 2, the dependent variable is return on assets (ROA), which is net income (item #172) divided by the book value of assets (item #6). In columns 3 and 4, the dependent variable is net profit margin (NPM), which is net income divided by sales (item #12). In columns 5 and 6, the dependent variable is sales growth, which is the growth in sales over the previous 5 years. In columns 7 and 8, the dependent variable is return on equity (ROE), which is net income divided by the book value of common stock. All dependent variables are industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. All dependent variables are trimmed at the 5th and 95th percentiles of their empirical distributions. In columns 1–4 and 7–8, the coefficients are multiplied by 100, and in columns 5 and 6, they are multiplied by 10. Columns 1, 3, 5, and 7 report the coefficient on the G-index, and columns 2, 4, 6, and 8 report the coefficients on interaction terms between the G-index and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. Standard errors are clustered at the industry level. The sample period is from 1990 to 2006. t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	ROA		NPM		Sales Growth		ROE	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
G-index	−0.066***		−0.108***		−0.064**		−0.010	
	(2.88)		(3.47)		(2.35)		(0.30)	
G-index × HHI (low)		−0.001		−0.011		−0.004		0.054
		(0.02)		(0.21)		(0.07)		(0.87)
G-index × HHI (medium)		−0.076**		−0.139**		−0.096***		−0.004
		(2.02)		(2.14)		(2.65)		(0.05)
G-index × HHI (high)		−0.137***		−0.192***		−0.109***		−0.099*
		(4.34)		(2.87)		(3.06)		(1.93)
HHI (medium)		0.877		1.518		1.414**		0.771
		(1.48)		(1.21)		(2.05)		(0.65)
HHI (high)		1.051*		1.633*		1.975***		1.926*
		(1.75)		(1.87)		(2.72)		(1.74)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	17,699	17,699	17,699	17,699	17,699	17,699	17,699	17,699
Adj. R^2	0.32	0.32	0.23	0.23	0.24	0.24	0.24	0.24

the 5th and 95th percentiles of their empirical distribution. We obtain similar results if we use different cutoffs, or if we use median regressions instead. All right-hand variables are lagged. The sample period is from 1990 to 2006.

Table VIII presents the results. (Robustness checks can be found in the Internet Appendix.) In columns 1 and 2, the dependent variable is ROA. The coefficient on the noninteracted G-index is −0.066 (t = 2.88), implying that weak governance firms have on average lower operating performance. The pattern across HHI terciles is the same as before. The coefficient on the

G-index is small (−0.001) and insignificant in the lowest HHI tercile, is larger (−0.076) and significant ($t = 2.02$) in the medium HHI tercile, and is largest (−0.137) and significant ($t = 4.34$) in the highest HHI tercile.

In columns 3 to 6, the dependent variable is either NPM or sales growth. The results are similar to our ROA results. In both cases, the coefficient on the noninteracted G-index is negative and significant, implying that weak governance firms have on average lower net profit margins and lower sales growth. Moreover, the coefficient on the G-index is always small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile. In columns 7 and 8, the dependent variable is ROE. Although the results are again similar, they are much weaker. In particular, the coefficient on the noninteracted G-index is small and insignificant, which is also what GIM find for the years 1990 to 1999. Importantly, however, the coefficient on the G-index is again monotonic across HHI terciles, and it is again large and significant in the highest HHI tercile.

V. Agency Costs of Weak Corporate Governance

Our firm value and operating performance results suggest that, absent competitive pressure from the product market, weak governance gives rise to agency costs. To gain a better understanding of the nature of these agency costs, we now explore in more detail the relationship between (i) governance and investment activity and (ii) governance and productive efficiency.

A. Capital Expenditures and Acquisition Activity

To examine the relationship between governance and investment activity, we use the same specification as in our operating performance regressions, except that the dependent variable is now either capital expenditures or some measure of acquisition activity. The sample period is again from 1990 to 2006.

Table IX shows the results. In columns 1 and 2, the dependent variable is capital expenditures (Compustat item #30) divided by total assets (item #6). The dependent variable is industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. To account for outliers, we trim the dependent variable at the 5th and 95th percentiles of its empirical distribution. As is shown, the coefficient on the noninteracted G-index is positive and significant, implying that weak governance firms have on average higher capital expenditures. Moreover, the coefficient on the G-index is small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile.

Capital expenditures may be a poor measure of investment activity if most of the activity comes in the form of acquisitions. To examine the relationship between governance and acquisitions, we construct various proxies for acquisition activity using data from the Securities Data Corporation's (SDC) database. In columns 3 and 4, the dependent variable is the sum of the value of all

Table IX

Capital Expenditures and Acquisition Activity

This table reports the coefficients from panel regressions of either capital expenditures or some measure of acquisition activity on an intercept, year and industry fixed effects, the G-index, and control variables. The control variables are the same as in Table VIII. In columns 2, 4, 6, 8, and 10, the G-index is interacted with HHI dummies, and HHI dummies are included as additional control variables. The G-index and the HHI dummies are defined in Tables I and V, respectively. All right-hand-side variables are lagged. In columns 1 and 2, the dependent variable is capital expenditures (Capex; Compustat item #30) divided by total assets (item #6). Capex is trimmed at the 5^{th} and 95^{th} percentiles of its empirical distribution and is industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. In columns 3 and 4, the dependent variable is the acquisition ratio, which is the sum of the value of all acquisitions made by a firm in a given year divided by the firm's average market capitalization in that year. In columns 5 and 6, the dependent variable is the acquisition count, which is the number of acquisitions made by a firm in a given year. In columns 7 and 8, the dependent variable is the acquisition likelihood, which is a dummy variable that equals one if the firm makes at least one acquisition during the year and zero otherwise. In columns 9 and 10, the dependent variable is CAR(−2, +2), which is the acquiring firm's 5-day cumulative abnormal return (CAR) around the acquisition announcement. CARs are computed by estimating the parameters of the market model over a 200-day period from event day −210 to event day −11, where the CRSP equally weighted return is used as the market return. Columns 3 and 4 are based on Tobit regressions, columns 5 and 6 are based on Poisson regressions, and columns 7 and 8 are based on Probit regressions. In columns 3–8, the R^2 is McFadden's pseudo R^2. All coefficients are multiplied by 100. Columns 1, 3, 5, 7, and 9 report the coefficient on the G-index, and columns 2, 4, 6, 8, and 10 report the coefficients on interaction terms between the G-index and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. Standard errors are clustered at the industry level. The sample period is from 1990 to 2006. t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Capex		Acquisition Ratio		Acquisition Count		Acquisition Likelihood		CAR(−2, +2)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
G-index	0.032**		1.176***		3.449***		2.256***		−0.074*	
	(2.35)		(4.38)		(3.78)		(4.48)		(1.67)	
G-index × HHI (low)		0.019		0.895		1.659		1.362		−0.060
		(0.96)		(1.59)		(0.91)		(0.98)		(0.78)
G-index × HHI (medium)		0.025		1.157**		4.008**		2.603**		−0.043
		(0.97)		(2.04)		(2.54)		(2.00)		(0.44)
G-index × HHI (high)		0.053**		1.495**		4.557**		2.832**		−0.124*
		(2.08)		(2.51)		(2.30)		(2.26)		(1.74)

(continued)

Table IX—*Continued*

	Capex		Acquisition Ratio		Acquisition Count		Acquisition Likelihood		CAR(−2, +2)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
HHI (medium)		0.083		−4.457		−2.980		−0.151		0.074
		(0.19)		(0.48)		(1.09)		(0.63)		(0.07)
HHI (high)		−0.171		−5.624		−2.524		−0.148		0.801
		(0.44)		(0.96)		(1.22)		(0.97)		(0.78)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regression type	OLS	OLS	Tobit	Tobit	Poisson	Poisson	Probit	Probit	OLS	OLS
Number of observations	17,355	17,355	20,208	20,208	20,208	20,208	20,208	20,208	4,426	4,426
Adj./pseudo R^2	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.02	0.02

acquisitions made by a firm in a given year divided by the firm's average market capitalization in that year ("acquisition ratio"). In columns 5 and 6, the dependent variable is the number of acquisitions made by a firm in a given year ("acquisition count"). In columns 7 and 8, the dependent variable is the likelihood of making an acquisition, which is a dummy variable that equals one if the firm makes at least one acquisition during the year and zero otherwise. Regardless of which proxy we use, we always obtain the same result: the coefficient on the noninteracted G-index is always positive and significant, implying that weak governance firms make on average more acquisitions. Moreover, and importantly, the coefficient on the G-index is always small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile.

That weak governance firms make more acquisitions does not necessarily imply that these firms destroy value. However, in a recent article, Masulis et al. (2007, MWX) show that high G-index acquirer firms experience significantly lower CARs around acquisition announcements than do low G-index acquirer firms. This result is noteworthy for two reasons. First, it suggests that weak governance firms make more *value-destroying* acquisitions. Second, because CARs measure *unexpected* changes in stock prices, the result also suggests that the market does not fully anticipate the negative valuation effects of weak governance. As MWX point out, their result is inconsistent with the argument of Core et al. (2006) that investors are not surprised and that, consequently, the abnormal return to the Democracy–Dictatorship hedge portfolio is likely driven by an omitted variable bias.[17]

For our purpose, the main question of interest is whether weak governance firms experience significantly lower CARs only in noncompetitive industries. To address this question, we consider all acquisitions made between January 1, 1990 and December 31, 2006. The acquisition data are from the SDC database. Using MWX's selection criteria (p. 1855), this leaves us with a total of 4,426 acquisitions. Our methodology is the same as in MWX. For each acquisition, we compute the 5-day bidder CAR during the event window (-2, $+2$), where event day 0 is the announcement date of the acquisition. To compute abnormal returns, we use the CRSP EW return as the market return and estimate the parameters of the market model from day -210 to day -11 before the event date.

Columns 9 and 10 of Table IX present the results. The coefficient on the noninteracted G-index is -0.074 ($t = 1.67$), implying that an increase in the G-index by one index point reduces acquirer shareholder wealth by 0.74%. Although this is slightly less than what MWX find (-0.096, $t = 2.22$), the discrepancy is likely due to differences in the sample period and the control variables. MWX consider the period from 1990 to 2003, while we consider the period from 1990 to 2006. In addition, MWX control for a large number of

[17] See MWX (pp. 1883–1884) for a discussion as well as Section III.F of this paper for further evidence that investors are negatively surprised about the poor operating performance of weak governance firms.

industry and deal characteristics, while we use the same specification as in our operating performance regressions. Importantly, however, the coefficient on the G-index is large (-0.124) and significant ($t = 1.74$) only in the highest HHI tercile, while it is otherwise small and insignificant. Thus, weak governance firms make more value-destroying acquisitions, but only in noncompetitive industries.

B. Labor Productivity and Cost Efficiency

An alternative hypothesis is that managers of poorly governed firms enjoy the "quiet life" by avoiding "cognitively difficult activities" (Bertrand and Mullainathan (2003)), such as fighting with labor unions, haggling with input suppliers, and expending effort to improve labor productivity. To explore this hypothesis, we again use the same specification as in our operating performance regressions, except that the dependent variable is now either labor productivity or some measure of cost efficiency. All dependent variables are industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. To account for outliers, we trim all dependent variables at the 5th and 95th percentiles of their empirical distribution. All right-hand variables are lagged. The sample period is again from 1990 to 2006.

Table X presents the results. In columns 1 and 2, the dependent variable is labor productivity, which is the logarithm of sales (Compustat item #12) divided by the number of employees (item #29) and deflated by the consumer price index from the U.S. Bureau of Labor Statistics. In columns 3 and 4, the dependent variable is costs of goods sold (item #41, "input costs") divided by sales. In both cases, we find similar results. The coefficient on the noninteracted G-index is either negative and significant (labor productivity) or positive and significant (input costs), implying that weak governance firms have on average lower labor productivity and higher input costs. Moreover, the coefficient on the G-index is small and insignificant in the lowest HHI tercile, is monotonic across HHI terciles, and is large and significant in the highest HHI tercile.

In columns 5 and 6, the dependent variable is real wages, which is the logarithm of labor and related expenses (item #42) divided by the number of employees and deflated by the consumer price index. Although the results are qualitatively similar, they are much weaker. In particular, the coefficient on the noninteracted G-index, although positive, is insignificant ($t = 1.61$). Also, the coefficient on the G-index in the highest HHI tercile, while almost twice as large as the coefficient in the lowest HHI tercile, is not significant ($t = 1.42$). That the results are weaker is not entirely surprising. Compustat wage data are extremely spotty. While some firms report wage data only intermittently, others report no wage data at all (see Bertrand and Mullainathan (1999)). As a consequence, the sample is considerably smaller and, furthermore, it is very noisy, making statistical inferences difficult.

In columns 7 and 8, the dependent variable is selling, general, and administrative expenses (item #189, "overhead costs") divided by total assets (item

Table X

Labor Productivity and Cost Efficiency

This table reports the coefficients from panel regressions of either labor productivity or some measure of cost efficiency on an intercept, year and industry fixed effects, the G-index, and control variables. The control variables are the same as in Table VIII. In columns 2, 4, 6, 8, and 10, the G-index is interacted with HHI dummies, and HHI dummies are included as additional control variables. The G-index and the HHI dummies are defined in Tables I and V, respectively. All right-hand-side variables are lagged. In columns 1 and 2, the dependent variable is labor productivity, which is the logarithm of sales (Compustat item #12) divided by the number of employees (item #29) and deflated by the consumer price index from the U.S. Bureau of Labor Statistics. In columns 3 and 4, the dependent variable is costs of goods sold (item #45) divided by sales (item #12). In columns 5 and 6, the dependent variable is real wages, which is the logarithm of labor and related expenses (item #42) divided by the number of employees and deflated by the consumer price index. In columns 7 and 8, the dependent variable is selling, general, and administrative expenses (SG&A; item #189) divided by total assets (item #6). In columns 9 and 10, the dependent variable is R&D expenditures (item #46) divided by total assets. All dependent variables are trimmed at the 5^{th} and 95^{th} percentiles of their empirical distributions and are industry-adjusted by subtracting the industry median in a given 48 FF industry and year. Industry medians are computed using all available Compustat firms. The coefficients in columns 3, 4, 7, 8, 9, and 10 are multiplied by 100. Columns 1, 3, 5, 7, and 9 report the coefficient on the G-index, and columns 2, 4, 6, 8, and 10 report the coefficients on interaction terms between the G-index and HHI dummies as well as the coefficients on the HHI dummies as control variables. The coefficients on the intercept and the other control variables are not reported for brevity. Standard errors are clustered at the industry level. The sample period is from 1990 to 2006. t-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Labor Productivity		Costs of Goods Sold		Wages		SG&A		R&D	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
G-index	−0.012***		0.236**		0.066		0.095		−0.052*	
	(3.66)		(2.47)		(1.61)		(0.96)		(1.75)	
G-index × HHI (low)		−0.008		0.140		0.051		0.045		−0.059
		(1.35)		(1.14)		(0.84)		(0.35)		(1.19)
G-index × HHI (medium)		−0.014**		0.228		0.059		0.117		−0.037
		(2.51)		(1.28)		(1.27)		(0.68)		(1.15)
G-index × HHI (high)		−0.015***		0.361**		0.090		0.101		−0.064
		(2.91)		(2.49)		(1.42)		(0.70)		(1.13)
HHI (medium)		0.044		−0.824		−0.126		−0.576		0.028
		(0.53)		(0.40)		(0.23)		(0.29)		(0.09)
HHI (high)		0.064		−2.160		−0.397		−0.611		0.619
		(0.91)		(1.27)		(0.46)		(0.33)		(0.86)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	17,387	17,387	17,699	17,699	2,249	2,249	13,672	13,672	9,340	9,340
Adj. R^2	0.16	0.16	0.11	0.11	0.79	0.79	0.15	0.15	0.17	0.17

#6). Here, the results are weak. Although the coefficient on the G-index in the highest HHI tercile is more than twice as large as the coefficient in the lowest HHI tercile, the pattern across HHI terciles is not monotonic. Besides, all coefficients are insignificant. In columns 9 and 10, the dependent variable is R&D expenditures (item #46) divided by total assets. As is shown, the coefficient on the noninteracted G-index is negative and significant, though it is not obvious how to interpret this result. It could be the case that poorly monitored managers reduce R&D as a means to reduce their risk exposure. Or it could simply be the case that poorly monitored managers place less value on research. Moreover, there is no systematic pattern across HHI terciles.

VI. Hedge Fund Activism

Our results suggest that weak governance firms have lower equity returns, worse operating performance, and lower firm value, but only in noncompetitive industries. In this final part of our analysis, we examine whether investors take actions to mitigate the inefficiency. In particular, we examine whether weak governance firms, especially those in noncompetitive industries, are more likely to be targeted by activist hedge funds.

Early studies of shareholder activism typically focus on the activist role of institutional investors, such as pension funds and mutual funds. These studies find little evidence that institutional investors bring about significant improvements in the companies they target (see Gillan and Starks (2007) for a review). More recent studies suggest that the opposite is true of activist hedge funds (Brav et al. (2008), Klein and Zur (2009)).[18] For instance, Brav et al. (2008) find that in the 2 years following an intervention by an activist hedge fund, the targeted company's ROA increases by 0.9 to 1.5 percentage points, and its operating profit margin increases by 4.7 to 5.8 percentage points.

To address whether weak governance firms, especially those in noncompetitive industries, are more likely to be targeted by activist hedge funds, we use the data by Brav et al. (2008). The data are based on Schedule 13D filings, which investors must file with the SEC within 10 days of acquiring more than 5% of any class of securities of a publicly traded company if they have an interest in influencing the company's management. The data include 1,059 hedge fund interventions from 2001 to 2006 involving 882 unique target companies. To examine the likelihood that a company is targeted by an activist hedge fund in the following year, we match the data with the merged Compustat/IRRC sample from 2000 to 2005. After removing firms with dual-class shares and missing SIC codes, the merged Compustat/IRRC sample during this period consists of 10,134 firm-year observations, of which 217 (or 2.14%) correspond to firms targeted by an activist hedge fund in the following year.

To examine how the likelihood of being targeted by activist hedge funds depends jointly on governance and competition, we sort firms into two governance groups based on whether the G-index lies above or below the median. We then divide each governance group into three equal-sized groups by ranking firms according to their HHIs and then sorting them into HHI terciles. Similar to what we did in our main analysis (see the Internet Appendix), we verify that our results are not driven by systematic differences in the HHI across the two governance groups. As Panel A of Table XI shows, the empirical distribution

[18] Brav et al. (2008) mention collective action problems, regulatory constraints, conflicts of interest, political constraints, and weak financial incentives as the main reasons why activist institutional investors, but not activist hedge funds, are unsuccessful at implementing their objectives.

Table XI

Hedge Fund Activism

Panel A sorts firms with above- and below-median G-index, respectively, into terciles based on their HHIs. For each HHI tercile, it shows the mean HHI, median HHI, and range of observed HHI values. The sample period is from 2000 to 2005. The G-index and the HHI are defined in Table I. Panel B shows the percentage of firms targeted by an activist hedge fund in the following year for each of the $2 \times 3 = 6$ groups from Panel A. The sample consists of 10,134 firm-year observations from 2000 to 2005, of which 217 observations correspond to firms targeted by an activist hedge fund in the following year. Panel C shows the change in the G-index following a hedge fund intervention for 127 interventions between 2000 and 2005. The change in the G-index is computed as the difference between the G-index published in the next available IRRC file after the intervention and the G-index published in the latest IRRC file prior to the intervention. (As the last IRRC file was published in January 2006, interventions in 2006 are excluded.) It is adjusted for general trends in the G-index by subtracting the average change in the G-index during the same time period based on all firms in the IRRC sample. In Panels B and C, the last row shows the difference between the above- and below-median G-index groups for any given HHI tercile, and the last column shows the difference between the highest and lowest HHI terciles for either the above- or below-median G-index group. *p*-values are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel A: Empirical Relation between the G-Index and the HHI

	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile
G-index > median			
Mean HHI	0.03	0.05	0.11
Median HHI	0.03	0.05	0.08
Range of HHI values	[0.02, 0.04]	[0.04, 0.06]	[0.06, 0.82]
G-index ≤ median			
Mean HHI	0.03	0.05	0.11
Median HHI	0.03	0.05	0.08
Range of HHI values	[0.02, 0.04]	[0.04, 0.06]	[0.06, 0.82]

Panel B: Percentage of Firms Targeted by Activist Hedge Funds

	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	Diff. in Means (Highest − Lowest)
G-index > median	1.90%***	2.93%***	3.14%***	1.24%**
	(0.000)	(0.000)	(0.000)	(0.029)
G-index ≤ median	1.51%***	1.78%***	1.85%***	0.34%
	(0.000)	(0.000)	(0.000)	(0.140)
Diff. in means	0.49%	1.15%**	1.29%**	
	(0.387)	(0.026)	(0.016)	

Panel C: Changes in the G-Index Following a Hedge Fund Intervention

	Lowest HHI Tercile	Medium HHI Tercile	Highest HHI Tercile	Diff. in Means (Highest − Lowest)
G-index > median	0.168	−0.104	−0.264*	−0.432*
	(0.303)	(0.242)	(0.054)	(0.073)
G-index ≤ median	0.146	−0.009	−0.104	−0.250
	(0.529)	(0.887)	(0.726)	(0.522)
Diff. in means	0.022	−0.095	−0.160	
	(0.935)	(0.401)	(0.606)	

of the HHI is the same in both governance groups. For instance, firms in the lowest HHI tercile of the high G-index group have a mean (median) HHI of 0.03 (0.03), as do firms in the lowest HHI tercile of the low G-index group.

Panel B reports the percentage of firms targeted by activist hedge funds for each of the $2 \times 3 = 6$ groups sorted by the G-index and the HHI. We obtain four main results. First, high G-index firms are more likely to be targeted than are low G-index firms, which is consistent with Brav et al. (2008, p. 1751). Second, the difference is monotonic across HHI terciles. It is small and insignificant in the lowest HHI tercile, is larger and significant in the medium HHI tercile, and is largest and significant in the highest HHI tercile. Thus, in competitive industries, governance does not significantly affect the likelihood of being targeted by activist hedge funds. In contrast, in noncompetitive industries, high G-index firms are significantly more likely to be targeted than are low G-index firms. Third, in each governance group, the percentage of firms targeted by activist hedge funds is monotonic across HHI terciles. Fourth, the difference between the lowest and highest HHI tercile is only significant in the high G-index group, while it is insignificant in the low G-index group. Hence, for firms with a low G-index, competition does not significantly affect the likelihood of being targeted. In contrast, for firms with a high G-index, those in noncompetitive industries are significantly more likely to be targeted than are firms in competitive industries.

We also examine whether being targeted by an activist hedge fund leads to a subsequent change in the G-index. For each hedge fund intervention, we compute the change in the G-index (ΔG) as the difference between the next available G-index and the G-index at the time of the intervention. To adjust for general trends in the G-index, we subtract the average change in the G-index during the same time period using all firms in the IRRC sample. Unfortunately, information on the next available G-index is missing for 90 of the 217 interventions in Panel B, which leaves us with 127 interventions.[19] This is arguably a small sample, especially as we sort firms into $2 \times 3 = 6$ groups, making it difficult to obtain statistically significant results.

Panel C reports the average ΔG for each of the $2 \times 3 = 6$ groups sorted by the G-index and the HHI. As can be seen, ΔG is only significant in one group, namely, the group with high G-index firms in the highest HHI tercile. Comparisons within each governance group yield stronger results. In both governance groups, ΔG is monotonic across HHI terciles. Moreover, and similar to our results in Panel B, the difference between the lowest and the highest HHI tercile is only significant in the high G-index group, while it is insignificant in the low G-index group. Thus, for firms with a low G-index, competition does not significantly affect changes in the G-index following a hedge fund intervention. In contrast, for firms with a high G-index, those in noncompetitive

[19] Of the 217 interventions, 61 occurred in 2006, which is after the latest IRRC file was published (January 2006). In the remaining 29 cases, the firm dropped out of the IRRC database after the intervention.

industries experience a significantly larger drop in the G-index than do firms in competitive industries.

VII. Conclusion

Economists often argue that managerial slack is first and foremost a problem for firms in noncompetitive industries. By implication, firms in competitive industries should benefit less from good governance, while firms in noncompetitive industries, where lack of competitive pressure fails to enforce discipline on managers, should benefit relatively more. Consistent with this argument, we find that weak governance firms, as measured by the G-index, have lower equity returns, worse operating performance, and lower firm value, but only in noncompetitive industries.[20] When we examine the causes of this inefficiency, we find that weak governance firms have lower labor productivity, higher input costs, and make more value-destroying acquisitions, but, again, only in noncompetitive industries. We also find that weak governance firms in noncompetitive industries are more likely to be targeted by activist hedge funds, suggesting that investors take actions to mitigate the inefficiency.

Our results have several important implications. On a practical level, our results imply that researchers might benefit from interacting governance proxies with measures of competition. In several cases, we found that the coefficient on the governance proxy is significant in noncompetitive industries, even though it is insignificant on average. Our results also imply that policy efforts to improve governance might benefit from focusing primarily on firms operating in noncompetitive industries. Moreover, such efforts could be broadened to also include measures aimed at improving an industry's competitiveness, such as deregulation and antitrust laws.

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[20] Our results suggest that managerial incentive schemes, if costly to the firm, should be weaker in competitive industries. This is consistent with Aggarwal and Samwick (1999), who find that (own-firm) pay-for-performance sensitivity is weaker for firms in more competitive industries.

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