

Value Enhancing Capital Budgeting and Firm-Specific Stock Return Variation

Art Durnev, Randall Morck, and Bernard Yeung*

* Durnev is from the University of Michigan Business School, Morck is the Stephen A. Jarislowsky Distinguished Professor of Finance at the School of Business, University of Alberta, and Yeung is the Abraham Krasnoff Professor of International Business, Professor of Economics, and Professor of Management at the Stern School of Business, New York University. We are grateful for helpful comments by the editor, Richard Green, an anonymous referee, Yakov Amihud, Luis Cabral, Serdar Dinc, William Goetzmann, David Hirshleifer, Bjørne Jørgensen, Andrew Karolyi, Han Kim, Claudio Loderer, JP Mei, Roberta Romano, Robert Shiller, Andrei Shleifer, Richard Sloan, Rene Stulz, Jeremy Stein, Richard Thaler, Larry White and Daniel Wolfenzon; and to participants at the NBER Corporate Finance Seminar, le Centre Interuniversitaire de Recherche en Analyse des Organisations (CIRANO) in Montreal, the Econometric Society meeting at the University of California in Los Angeles, the European Financial Management Association meeting in Lugano, Baruch-CUNY, Columbia Business School, Indiana University, the University of Alberta, the University of Michigan, the University of Minnesota, MIT Sloan School, New York University, the Ohio State University, the University of North Carolina, the University of Chicago, and Yale University; and to students in Andrei Shleifer's Research Seminar on Behavioral Finance at Harvard.

Value Enhancing Capital Budgeting and Firm-Specific Stock Return Variation

Abstract

We document a robust cross-sectional positive association across industries between a measure of the economic efficiency of corporate investment and the magnitude of firm-specific variation in stock returns. This finding is interesting for two reasons, neither of which is a priori obvious. First, it adds further support to the view that firm-specific return variation gauges the extent to which information about the firm is quickly and accurately reflected in share prices. Second, it can be interpreted as evidence that more informative stock prices facilitate more efficient corporate investment.

Corporate capital investment should be more efficient where stock prices are more informative. Informed stock prices convey meaningful signals to management about the quality of their decisions. They also convey meaningful signals to the financial markets about the need to intervene when management decisions are poor. Corporate governance mechanisms, such as shareholder lawsuits, executive options, institutional investor pressure, and the market for corporate control, depend on stock prices. Where stock prices are more informative, these mechanisms induce better corporate governance – which includes more efficient capital investment decisions.

Our objective in this paper is to examine empirically whether capital investment decisions are indeed more efficient where stock prices are more informative. To do this, we require a measure of the efficiency of investment and a measure of the informativeness of stock prices.

To gauge the efficiency of corporate investment, we directly estimate Tobin's marginal q ratio, the change in firm value due to unexpected changes in investment scaled by the expected change in investment, for U.S. industries. The deviation of Tobin's marginal q from its optimal level is our measure of investment efficiency – the smaller the deviation the greater the investment efficiency.

To gauge the informativeness of stock prices, we follow Morck, Yeung and Yu (2000) and consider the magnitude of firm-specific return variation. We justify this on two grounds: one conceptual and the other empirical. On the conceptual level, stock variation occurs because of trading by investors with private information. Grossman and Stiglitz (1980) predict that a lower cost of private information leads to a higher intensity of informed trading, and hence to what they call “more informative pricing.” Extending their reasoning, we suggest that, in a given time interval and all else equal, higher firm-specific variation stems from more intensive informed trading due to a lower cost of information, and hence indicates a more informative price. We focus on firm-specific

variation because Roll (1988) shows this could be associated with trading based on private information. On the empirical level, a growing empirical literature links firm-specific variation to stock price informativeness, e.g., Morck, Yeung and Yu (2000), Durnev et al. (2001), and Bushman, Piotroski, and Smith (2002). We recognize that these conceptual arguments and empirical studies, which we discuss in detail in the next section, constitute a subtle case for accepting firm-specific return variation as a proxy for stock price informativeness that calls for further theoretical development. However, we feel they nonetheless justify further investigation of this possibility.

We find the proximity of marginal q to its optimal level and the magnitude of firm-specific return variation to be highly positively correlated across industries. This finding is notable for two reasons. First, it underscores the conceptual arguments and empirical evidence cited above, that firm-specific stock return variation merits serious consideration as a measure of the informativeness of stock prices. Second, taking firm-specific variation as a measure of the informativeness of stock prices, it can be interpreted as evidence that informativeness of stock prices facilitates efficient investment. That is, the information efficiency of the stock market matters to the real economy.

While we cannot categorically reject alternative possible explanations of our finding, we believe them to be less plausible. One possibility is that firm-specific variation and the deviation of marginal q from its optimum might have common factors having nothing to do with the informativeness of stock prices. We include a long list of control variables, introduced in Section III, to capture such factors. Our empirical results in Section IV lead us to exclude the most obvious of these possibilities. Another more abstruse possibility is that high firm-specific variation is noise or, in the words of Roll (1986), “frenzy unrelated to concrete information.” In Section IV, we explore this possibility and ultimately reject it. Intuitively, our measure of the efficiency of capital investment decisions is actually a measure of how closely investment spending matches a change in

market value. If firm-specific variation reflects investor frenzy, our finding has the disturbing implication that capital spending is better aligned with market value change where market values are less meaningful. We are not aware of any theoretical basis for postulating that managers' capital budgeting decisions are most aligned with observed market value change when market value is noisier. We cannot preclude the possibility that further work might expose a missing factor in our statistical work, or might lead to a theory that explains why capital budgeting decisions are more aligned with observed market value changes when stock prices are noisier. However, we believe Ockham's razor disfavors these lines of attack.

Our paper is arranged as follows. Section I describes our firm-specific return variation variables, while Section II explains our marginal q measure. Section III describes our empirical estimation techniques and our main control variables. Section IV presents our empirical results and robustness checks. Section V considers the validity and implications of our interpretations of our results and Section VI concludes. The Appendix describes our data and marginal q estimation technique in detail.

I. Measuring Firm-Specific Return Variation

A. Motivation

We support our use of firm-specific return variation to measure stock price informativeness with a conceptual argument and with a body of empirical evidence.

On the conceptual level, variation in a firm's stock return in any given time period is due to public news and to trading by investors with private information. Grossman and Stiglitz (1980, p. 405) argue that "because [acquiring private] information is costly, prices cannot perfectly reflect the information which is available, since if it did, those who spent resources to obtain it would receive no

compensation.” In their model, traders invest in a risk-free asset and a single risky asset, and decide whether or not to pay for private information about the fundamental value of the risky asset. Grossman and Stiglitz derive the result that informed trading becomes more prevalent as the cost of private information falls, which increases the informativeness of the price system (p.399). We take this reasoning a step further, and suggest the following: In a market with many risky stocks, during any given time interval, information about the fundamental values of some firms might be cheap, while information about the fundamental values of others might be dear. Traders, *ceteris paribus*, obtain more private information about the former and less about the latter. Consequently, the stock prices of the former, moving in response to informed trading, are both more active and more informative than the stock prices of the latter.

Consider decomposing the variation of a firm’s return into a systematic portion, explained by market and industry return, and a firm-specific residual variation. Roll (1988) shows that firm-specific variation, so defined, is largely unassociated with public announcements, and argues that firm-specific return variation is therefore chiefly due to trading by investors with private information. Accordingly, even if the argument of Grossman and Stiglitz (1980) were not applicable to “free” macroeconomic information such as trade or money supply statistics, it surely applies to much of the firm-specific information. Thus, if the cost of firm-specific information varies across firms, *ceteris paribus*, the intensity and completeness of trading on private firm-specific information should also vary. Extending the argument of Roll (1988), we hypothesize that greater firm-specific variation indicates more intensive informed trading and, consequently, more informative pricing.

Empirically, a range of evidence already points in this direction.

First, Figure 1 shows the average R^2 statistics of regressions of firm-level stock return on local and U.S. market return using 1995 data for a range of countries, as reported by Morck, Yeung, and

Yu (2000). These R^2 's are very low for countries with well-developed financial systems, such as the United States, Canada, and the United Kingdom, but are very high for emerging markets such as Poland and China. Morck, Yeung, and Yu (2000) show that these results are clearly not due to differences in country or market size, and that they are unlikely to be due to more synchronous fundamentals in emerging economies. They find that government disrespect of private property rights and lack of shareholder protection laws actually explain the low level of firm-specific stock return variation. They propose that in countries with less corruption and better shareholder protection, traders have more incentive to trade based on firm-specific information. This is consistent with the argument that low average market model R^2 's reflect greater activity by the informed traders, as posited by Roll (1988).

[Figure 1 here]

Second, Wurgler (2000) shows capital flows to be more responsive to value-added in countries with less synchronous stock returns. This suggests that capital moves faster to its highest value uses where stocks move more asynchronously. That is, stock markets in which firm-specific variation is a larger fraction of total variation are more functionally efficient in the sense of Tobin (1982).

Third, Bushman, Piotroski, and Smith (2002) show that stock returns exhibit greater firm-specific return variation in countries with more developed financial analysis industries and with a freer press.

Fourth, Durnev et al. (2001) show that stock returns predict future earnings changes more accurately in industries with less synchronous returns, as measured by market-model R^2 statistics. Collins, Kothari, and Rayburn (1987), and others in the accounting literature, regard such predictive

power as gauging the “information content” of stock prices. In this sense, stock prices have greater information content when firm-specific variation is a larger fraction of total variation.

We believe these conceptual arguments and empirical results justify the use of firm-specific return variation as an indicator of timely and accurate incorporation of firm-specific information into stock prices. However, we realize that this view is based on theoretical conjecture and indirect empirical evidence. Indeed, Roll (1988) allows that firm-specific return variation may be due to “investors’ frenzy,” unrelated to information. We therefore remain ecumenical at the outset, and ultimately let the data suggest an interpretation of firm-specific return variation.

B. Measuring Firm-specific Return Variation

This section describes the estimation of our firm-specific return variation measures. We use daily total returns for 1990 through 1992 for the 4,029 firms in the intersection of CRSP and COMPUSTAT. These span 196 three-digit SIC industries. Appendix provides further details. Since we estimate our other important variable, the efficiency of corporate investment decisions, using a 1993-to-1997 panel of annual data for each industry, estimating industry-average firm-specific variations over this period lets us match pre-determined firm-specific return variation of an industry with the same industry’s investment efficiency measure, and thereby mitigate endogeneity problems.

We gauge firm-specific return variation by regressing firm j ’s return on industry i , $r_{i,j,t}$, on market and industry returns, $r_{m,t}$ and $r_{i,t}$, respectively:

$$r_{i,j,t} = \beta_{j,0} + \beta_{j,m}r_{m,t} + \beta_{j,i}r_{i,t} + \varepsilon_{i,j,t} \quad [1]$$

where $\beta_{j,0}$ is the constant, $\beta_{j,m}$ and $\beta_{j,i}$ are regression coefficients and $\varepsilon_{i,j,t}$ is the noise term. The market index and industry indices are value-weighted averages excluding the firm in question. This exclusion prevents spurious correlations between firm and industry returns in industries that contain few firms. One minus the average R^2 of [1] for all firms in an industry measures the importance of

firm-specific return variation in that industry. We use industry aggregate rather than firm-level estimates to facilitate comparison with our marginal q estimates which we shall explain below.

Note that we follow Roll (1988) in distinguishing “firm-specific” variation from the sum of market-related and industry-related variation. For simplicity, we refer to the latter sum as “systematic” variation. We decompose return variation in this way because Roll (1988) specifically links arbitrage that capitalizes private information to firm-specific variation, so defined.

A standard variance decomposition lets us express an industry-average R^2 as

$$R_i^2 = \frac{\sigma_{m,i}^2}{\sigma_{\varepsilon,i}^2 + \sigma_{m,i}^2}, \quad [2]$$

where

$$\begin{aligned} \sigma_{\varepsilon,i}^2 &= \frac{\sum_{j \in i} SSR_{i,j}}{\sum_{j \in i} T_j} \\ \sigma_{m,i}^2 &= \frac{\sum_{j \in i} SSM_{i,j}}{\sum_{j \in i} T_j} \end{aligned} \quad [3]$$

for $SSR_{i,j}$ and $SSM_{i,j}$, the unexplained and explained variations of [1], respectively. The sums in [3] are scaled by $\sum_{j \in i} T_j$, the number of daily observations available in industry i .

Since $\sigma_{\varepsilon,i}^2$ and $\sigma_{m,i}^2$ have skewness of 2.27 and 3.51, respectively, and kurtoses of 9.76 and 19.93, respectively, we apply a logarithmic transformation. Both $\ln(\sigma_{\varepsilon,i}^2)$ and $\ln(\sigma_{m,i}^2)$ are more symmetric (*skewness* = -0.37, 0.07) and normal (*kurtosis* = 3.66, 3.52).

The distribution of $1 - R_i^2$ is also negatively skewed (*skewness* = -1.00) and mildly leptokurtic (*kurtosis* = 4.79). Moreover, it has the econometrically undesirable characteristic of being bounded

within the unit interval. As recommended by Theil (1971, chapter 12), we circumvent the bounded nature of R^2 with a logistic transformation of $1 - R_i^2 \in [0,1]$ to $\Psi_i \in \mathfrak{R}$,

$$\Psi_i = \ln\left(\frac{1 - R_i^2}{R_i^2}\right). \quad [4]$$

We thus use the Greek letter *psi* to denote firm-specific stock return variation measured relative to variations due to industry- and market-wide variation. The transformed variable is again less skewed (*skewness* = 0.03) and less leptokurtic (*kurtosis* = 3.80). The hypothesis that Ψ_i is normally distributed cannot be rejected in a standard W-test (*p-value* = 0.13).

The transformed variable Ψ_i also possesses the useful characteristic that

$$\Psi_i = \ln\left(\frac{1 - R_i^2}{R_i^2}\right) = \ln\left(\frac{\sigma_{\varepsilon,i}^2}{\sigma_{m,i}^2}\right) = \ln(\sigma_{\varepsilon,i}^2) - \ln(\sigma_{m,i}^2). \quad [5]$$

Intuitively, a higher Ψ_i indicates the greater the power of firm-specific variation, $\sigma_{\varepsilon,i}^2$, relative to market and industry-wide variation, $\sigma_{m,i}^2$, in explaining the stock price movements of firms in industry *i*.

We let $\ln(\sigma_{\varepsilon,i}^2)$ denote *absolute firm-specific stock return variation*, $\ln(\sigma_{m,i}^2)$ *absolute systematic stock return variation*, and Ψ_i *relative firm-specific stock return variation*.

Table I briefly describes these variables, and others used in this study. Panel A of Table II presents univariate statistics for $\ln(\sigma_{\varepsilon,i}^2)$, $\ln(\sigma_{m,i}^2)$ and Ψ_i . The substantial standard deviations and spreads of these three variables attest to their substantial variation across industries. Moreover, higher firm-specific and systematic return variations tend to occur together ($\rho = 0.773$, *p-val* = 0.00).¹

[Table I here]

[Table II here]

II. Tobin's Marginal q Ratio

A. Motivation

We now turn to our measure for the proximity of capital budgeting to value maximization. Optimal capital budgeting requires undertaking all positive expected net present value (NPV) projects and avoiding all those with negative expected NPV. The NPV of a project is the present value of the net cash flows, cf_t . The project will produce at all future times t less its set-up cost, C_0 . Thus, optimal capital budgeting requires undertaking projects if and only if

$$E[NPV] = E\left[\sum_{t=1}^{\infty} \frac{cf_t}{(1+r)^t} - C_0\right] > 0 \quad [6]$$

where E is the expectations operator. Under ordinary circumstances, managers are the decision makers, and the E operator should be based on the manager's information set.

To compare NPVs across firms, we scale by set-up cost, obtaining profitability indexes (PI). Optimality entails undertaking a project if and only if its expected PI surpasses one,

$$E_{mgt}[PI] = \frac{1}{C_0} E_{mgt}\left[\sum_{t=1}^{\infty} \frac{cf_t}{(1+r)^t}\right] = 1 + \frac{E_{mgt}[NPV]}{C_0} > 1, \quad [7]$$

where we now explicitly use E_{mgt} to denote management's expectations.

The change in the market value of a firm associated with an unexpected unit increase in its stock of capital goods (replacement cost) is the firm's marginal Tobin's q ratio, and is denoted

$$\dot{q} = \frac{\Delta V}{\Delta K} = \frac{1}{C_0} E\left[\sum_{t=1}^{\infty} \frac{cf_t}{(1+r)^t}\right] = 1 + \frac{E[NPV]}{C_0} = E[PI], \quad [8]$$

where all capital spending during each year is aggregated into a project with set-up cost C_0 , cf_t is the total cash flows this project yields at times t , and E here reflects investors' expectations.

Thus, marginal q is investors' estimate of the marginal project's profitability index. Ignoring taxes and other complications, value-maximization implies $\hat{q} = 1$. In this idealized situation, $\hat{q} > 1$ implies underinvestment and $\hat{q} < 1$ implies overinvestment. We discuss the effects of taxes and other complexities on the threshold \hat{q} , here denoted h , after we have explained our estimation of \hat{q} .

B. Measuring Tobin's Marginal q Ratio

We now summarize our estimation procedure (a full description is provided in the Appendix).

We operationalize [8] by writing the marginal q of firm j as the ratio

$$\hat{q}_{j,t} = \frac{V_{j,t} - E_{t-1}V_{j,t}}{A_{j,t} - E_{t-1}A_{j,t}} = \frac{V_{j,t} - V_{j,t-1}(1 + \hat{r}_{j,t} - \hat{d}_{j,t})}{A_{j,t} - A_{j,t-1}(1 + \hat{g}_{j,t} - \hat{\delta}_{j,t})}, \quad [9]$$

where $V_{j,t}$ and $A_{j,t}$ are the market value (equity plus debt) and stock of capital goods, respectively, of firm j at time t , and E_t is the expectations operator using all information extant at time t .² The expected market value of the firm in t is its market value in $t-1$ augmented by both the expected return from owning the firm, $\hat{r}_{j,t}$, and its disbursements to investors, $\hat{d}_{j,t}$, which includes cash dividends, share repurchases, and interest expenses.³ The expected value of the firm's capital assets in period t is the value of its capital assets in period $t-1$ augmented by both its expected rate of spending on capital goods, $\hat{g}_{j,t}$, and the expected depreciation rate on those capital goods, $\hat{\delta}_{j,t}$.

Cross-multiplying and simplifying [9] leads to

$$\frac{V_{j,t}^i - V_{j,t-1}^i}{A_{j,t-1}^i} = -\hat{q}_j(g_j - \delta_j) + \hat{q}_j \frac{A_{j,t}^i - A_{j,t-1}^i}{A_{j,t-1}^i} + r_j \frac{V_{j,t-1}^i}{A_{j,t-1}^i} + \xi_j \frac{D_{j,t}^i}{A_{j,t-1}^i} + u_{j,t}^i, \quad [10]$$

where $D_{j,t}^i \equiv \hat{d}_{j,t} V_{j,t-1}^i$ and ξ allows for a tax wedge. (Theoretically, ξ should be equal to negative one. However, the valuation of dividends, share repurchases and bond interest payments may be

different from market value changes because of the difference in the tax brackets of various recipients of disbursement.)

It follows that the coefficient β_0^i of the regression across all firms j in industry i at times t

$$\frac{\Delta V_{j,t}^i}{A_{j,t-1}^i} = \alpha^i + \beta_0^i \frac{\Delta A_{j,t}^i}{A_{j,t-1}^i} + \beta_1^i \frac{V_{j,t-1}^i}{A_{j,t-1}^i} + \beta_2^i \frac{D_{j,t}^i}{A_{j,t-1}^i} + u_{j,t}^i \quad [11]$$

is an estimate of an industry-average marginal q . We estimate [11] using the Generalized Least Squares method to allow error correlation across time for each firm and across firms in each period.

To relate \hat{q} to predetermined firm-specific variation (measured over 1990 to 1992), we estimate [11] using a 1993-to-1997 panel of annual data for each industry. We use industry, not firm-level, \hat{q} estimates for two reasons. First, firm-level estimation of [11] requires many years of data, inducing a survival bias. Second, using long time windows means that shifting technological constraints, market conditions, and governance changes might make our estimates unreliable. Since non-synchronous $\Delta V_{j,t}^i$ and $\Delta A_{j,t}^i$ can add noise, we define the change in firm value according to a firm's fiscal-year window.⁴

The average estimated α^i , β_1^i , and β_2^i also broadly match their interpretations in [10]. The mean and median $\alpha^i = -\hat{q}_j(g_{j,t} - \delta_{j,t})$ are -0.129 and -0.089 , respectively, and α^i differs insignificantly from zero (p -value $< 10\%$) in 110 of 196 industries. Also, α^i is negatively and significantly correlated with estimated growth rates of capital assets. The mean β_1^i , 0.127 , implies an average cost of capital of 12.7 percent, the median β_1^i is 0.129 . The second regression coefficient, β_1^i , is significantly positively correlated with estimated weighted average costs of capital. The mean and median β_2^i are -0.680 and -0.668 , respectively; β_2^i differs significantly from negative one (p -value $< 10\%$) in 146 of 196 industries.

The sample mean \hat{q} is 0.91, and the median is 0.87.⁵ The correspondence of capital budgeting to value maximization depends on the distance of \hat{q} from its optimal value, h , which we initially set to one. We measure the distance of \hat{q} from h as either a squared deviation, $(\hat{q} - h)^2$, or an absolute deviation, $|\hat{q} - h|$. For simplicity, we say $(\hat{q} - h)^2$ and $|\hat{q} - h|$ gauge *capital budgeting quality*, though they are more properly regarded as measuring investors' aggregated opinions about capital budgeting quality; that is, their opinions about corporate investment efficiency. Panel B of Table II provides summary statistics of \hat{q} , $(\hat{q} - 1)^2$ and $|\hat{q} - 1|$ for our 196 industries.

C. Complications

Taxes and other complications can push h , the optimal value of the estimated \hat{q} , away from one. (Let the optimal value of the estimated \hat{q} be \hat{q}). In this section, we consider these complications, and discuss their importance in this analysis.

First, h may deviate from one because of taxes. Suppose a firm unexpectedly increases its stock of capital assets by plowing back $(A_{j,t} - E_{t-1}A_{j,t})$ of after-tax corporate earnings. The cost to investors of the firm not disbursing this is $(1 - T_D)(A_{j,t} - E_{t-1}A_{j,t})$, where T_D is the personal tax on disbursements. This gives investors an after-tax capital gain of $(1 - T_{CG})(V_{j,t} - E_{t-1}V_{j,t})$, where T_{CG} is the effective personal capital gains tax rate, adjusted for the timing of realizations. For this capital investment to add value, $(1 - T_{CG})(V_{j,t} - E_{t-1}V_{j,t})$ must exceed $(1 - T_D)(A_{j,t} - E_{t-1}A_{j,t})$. Repeating the algebra used to derive [10] now yields

$$\frac{V_{j,t}^i - V_{j,t-1}^i}{A_{j,t-1}^i} = \alpha_j + \hat{q}_j \frac{1 - T_D}{1 - T_{CG}} \frac{A_{j,t}^i - A_{j,t-1}^i}{A_{j,t-1}^i} + r_j \frac{V_{j,t-1}^i}{A_{j,t-1}^i} + \xi_j \frac{D_{j,t}^i}{A_{j,t-1}^i} + u_{j,t}^i. \quad [12]$$

This means that β_1^i from [11] is actually an estimate of $\hat{q}_j \left(\frac{1 - T_D}{1 - T_{CG}} \right)$. Reasonable figures for the 1990s are $T_D \cong 33$ percent and $T_{CG} \cong 14$ percent (half the statutory rate of 28 percent). Assuming the marginal investor is tax-exempt half of the time, these assumptions imply that $\hat{q} \cong 1.15 \beta_1^i$, moving our mean \hat{q} to $0.91 \times 1.15 = 1.05$, and the median to $0.87 \times 1.15 = 1.00$.

Needless to say, this comparison is further clouded by the corporate tax advantages from various sorts of capital spending, the endogeneity of capital structure and disbursement policies, the timing of capital gains realization, the substitution of repurchases for dividends, and the wide range of personal tax rates paid by different investors.

Second, capital spending is disclosed annually (unaudited quarterly data are less reliable), so the aggregation of projects in [9] is unavoidable. If, as conditions change differentially, firms continuously adjust their capital budgeting, \hat{q} should be near one. However, if discrete changes induce large capital budgeting changes, [9] may capture effects on value of infra-marginal, as well as marginal, capital spending. This should bias \hat{q} and h upward.

Third, C_0 (in [8]) is *unexpected* capital spending, but this is unobserved. In our operationalization in [9], we depict C_0 as observed capital spending minus an implicit estimate of expected capital spending. This estimate may be high or low, and thus induces noise, but not bias, in \hat{q} and hence h .

Fourth, changes in firm value, ΔV , may arise from changes in the values of past investments or future investment options. This adds noise, but not necessarily bias - unless, for example, such options rise in value throughout our estimation window, inducing an upward bias in \hat{q} and h for growth industries.

A priori, predicting the net effect of these complications is virtually impossible. However, since each affects observed \hat{q} and thus h similarly, the distances between \hat{q} and h may well still be meaningful, and these are the quantities of primary interest to us.

III. Empirical Framework

Our empirical objective is to examine the relationship between firm-specific return variation and the alignment of capital budgeting to market value maximization. As we stated in Section II.A, where we motivate the use of firm-specific return variation as a measure for stock price informativeness, this variable could conceivably reflect either more or less informed stock prices. In the former case, greater firm-specific variation should be associated with an estimated marginal q , β_0^i in [11], closer to its theoretical optimum; the opposite should hold in the latter case.

Our \hat{q} estimates could be affected by a variety of industry factors. Therefore, we must introduce a set of control variables. In this section, we first report simple correlations and then describe the control variables we use in our regressions.

A. Simple Correlation Coefficients

Table IIIa reports the simple correlation coefficients between our capital budgeting quality measures and our firm-specific stock return variation variables. Ignoring for the moment taxes and other complications, we interpret $(\hat{q} - 1)^2$ and $|\hat{q} - 1|$ as indicators of the deviation of capital budgeting from the optimum.⁶ Marginal q tends to be nearer one in industries where returns exhibit both greater absolute firm-specific variation, $\ln(\sigma_{\varepsilon,i}^2)$, and greater relative firm-specific variation, Ψ_i . These relationships are statistically significant. Also, the distance of \hat{q} from one is insignificantly related to systematic variation, $\ln(\sigma_{m,i}^2)$; \hat{q} itself is uncorrelated with all three return variation measures,

$\ln(\sigma_{\varepsilon,i}^2)$, $\ln(\sigma_{m,i}^2)$, and Ψ_i .⁷

[Table III here]

Figure 2 illustrates these patterns by grouping industries by their average R^2 s. Regardless of whether we use the mean absolute or squared distance of \dot{q} from one, \dot{q} is nearer to one in industries with lower R^2 s. Figure 3 shows that this pattern reflects a greater dispersion of \dot{q} *both above and below one* in industries with higher R^2 s.

[Figures 2 and 3 here]

B. Multivariate Regression Specification

The simple correlations and graphical representations of our data suggest that greater firm-specific return variation is associated with higher quality capital budgeting. To verify whether greater firm-specific return variation is associated, *ceteris paribus*, with capital budgeting quality, we control for other relevant factors.

Our regressions are thus of the form

$$\begin{aligned} \text{either } (\dot{q}_i - h)^2 \text{ or } |\dot{q}_i - h| &= b_\Psi \Psi + \mathbf{c}' \cdot \mathbf{Z}_i + u_i, \\ \text{either } (\dot{q}_i - h)^2 \text{ or } |\dot{q}_i - h| &= b_\varepsilon \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i + u_i, \end{aligned} \tag{13}$$

where \mathbf{Z}_i is a list of control variables. To mitigate endogeneity problems, the controls – like return variation – are measures over the period 1990 through 1992. Absolute systematic variation, $\ln(\sigma_{m,i}^2)$, as explained below, is also considered a control.

We begin by setting h to one. As discussed above, taxes, the discreteness of capital budgeting, the unobservability of expected capital spending, and changes in expected cash flows from prior or future investments can all push both estimated \dot{q} and h up or down. We therefore re-estimate [13] using nonlinear least squares to determine h and the regression coefficients

simultaneously. Appendix II and Amemiya (1985) provide details.

C. Control Variables

The controls are intended to capture several possibilities. First, exogenous factors might affect the quality of capital budgeting. For example, capital budgeting decisions might be better in concentrated industries with high barriers to entry because conditions in such industries are easier to predict. Not controlling for this obscures the true relationship between capital budgeting quality and firm-specific return variation by inducing heteroskedastic residuals. Although we use heteroskedasticity-consistent standard errors, including controls where possible is econometrically desirable.

Second, latent common factors related to both capital budgeting quality and firm-specific return variation might cause a spurious relationship between the two. Industry concentration again illustrates. Concentrated industries, in addition to having better quality capital budgeting decisions, might also contain homogenous firms whose fundamentals (and therefore stock returns) exhibit relatively little firm-specific variation. A negative relationship between capital budgeting quality and firm-specific return variation might simply reflect the effects of industry concentration on both variables. Several such latent common factors could affect capital budgeting quality and fundamentals variation.

Note that we do not include corporate governance variables, such as board structure, ownership structure, and the like. Corporate governance variables are themselves rough proxies for the alignment of corporate decision-making with market value maximization, which we estimate directly (at least with regard to capital budgeting) with \hat{q} . Including corporate governance variables would amount to putting proxies for our dependent variable on the right-hand side of our regressions.

We relegate the examination of the relationship between corporate governance variables, capital budgeting quality and firm-specific variation to future research.

The next two subsections describe our controls and our reasons for including each.

C.1 Specialized Control Variables

First, as argued above, industry concentration might matter. We therefore include a 1990-to-1992 average real sales-weighted *Herfindahl Index*, denoted H_i .

Second, we control for industry size. Firms in large, established industries might have more internal cash, greater access to capital, and fewer value-creating investment opportunities. They might therefore be more prone to the overinvestment problems of Jensen (1986) than firms in smaller industries. Also, larger industries may be more mature, contain more homogenous firms, and so exhibit less firm-specific fundamentals variation. Firms in smaller industries might be subject to greater information asymmetry problems, and thus be more likely to ration capital and underinvest. We therefore include the logarithm of 1990-to-1992 industry property, plant, and equipment (PP&E), denoted $\ln(K_i)$, as our *Industry Size* control. The estimation of K_i is explained in detail in the Appendix equations [A6] and [A7].

Third, a large literature links corporate diversification with both corporate governance problems and access to capital.⁸ Also, corporate diversification might also reduce firm-specific fundamentals variation. Our *Corporate Diversification* measure for industry i , denoted $segs_i$, is the 1990-to-1992 assets-weighted average diversification level of firms whose primary business is industry i . Firm diversification is the 1990-to-1992 average number of different 3-digit segments reported in COMPUSTAT Industry Segment file.

Fourth, capital budgeting might be more error-prone in industries where intangible assets are important because the future cash flows they generate are harder to predict. Moreover, firms in these

industries typically have fewer collateralizable assets, and thus may have more difficulty raising external funds. Also, Shiller (1989) implies that such firms might sometimes exhibit less firm-specific variation, as during R&D races, and then large firm-specific variation when one wins. We therefore control for industry *Research and Development Spending* (R&D) and *Advertising Spending*, denoted *r&d* and *adv* respectively. Both are measured per dollar of tangible assets in each industry, averaged across 1990 to 1992. Tangible assets are PP&E plus inventories, estimated as in Appendix equation [A5] and the description that follows. We take R&D to be negligible if not reported and all other financial data are reported.

Fifth, we control for average Tobin's q , the market value, $V_{j,t}$, over replacement cost, $A_{j,t}$,

$$\bar{q}_{j,t} \equiv \frac{V_{j,t}}{A_{j,t}}, \quad [14]$$

estimated using 1990 to 1992 data. Besides serving as a general proxy for the presence of intangibles, \bar{q} also measures the importance of growth options. Changes in these option values during our estimation window could affect both \dot{q} and σ_ε^2 . Note that \bar{q} is not the same as \dot{q} , marginal q . As a firm invests in ever more marginally value-increasing projects, its \dot{q} falls to one. Its average q , however, need not fall to one, for \bar{q} is investors' expected present value of cash flows from all its capital investments – including past inframarginal investments and future expected investments – scaled by the sum of the replacement costs of its existing assets.

To estimate each industry's \bar{q} , we sum the market values of all firms in that industry, and divide this by the sum of all their replacement costs. The market value and the replacement costs of tangible assets are as described in the Appendix. We then average this for each industry over 1990 to 1992. Although \bar{q} is uncorrelated with \dot{q} and negatively (insignificantly) correlated with \dot{q} 's

deviation from one, it is positively significantly related to both absolute and relative firm-specific return variation, measured by $\ln(\sigma_e^2)$ and Ψ .

Sixth, liquidity could affect capital budgeting decisions. For example, cash-rich firms might overinvest, while cash-strapped firms might ration capital. We therefore include industry *Liquidity*, 1990-to-1992 industry average net current assets over PP&E, denoted λ_i .

Seventh, the existing capital structure might affect capital budgeting. For example, Jensen (1986) argues that high leverage improves corporate governance - in part, by preventing overinvestment. Others, such as Myers (1977), argue that various bankruptcy cost constraints distort capital budgeting in highly levered firms. Since leverage might also affect fundamentals variation, we include *Leverage*, lev_i , 1990-to-1992 industry average long-term debt over tangible assets (PP&E and real inventory). Details of the estimation of long-term debt and tangible assets are provided in Appendix I.b.

Eighth, capital budgeting quality may be affected by industry-specific factors, which the above controls do not fully capture. We therefore add one-digit industry fixed effects.

C.2 Firm-specific Fundamentals Variation Control Variables

Unfortunately, myriad industry characteristics might affect firm-specific fundamentals variation, and many cannot be measured readily. Therefore, we explicitly control for firm-specific fundamentals variation with two proxies – a precisely estimated, but indirect measure, and a direct measure that can be estimated only imprecisely.

Firm-specific changes in fundamental value may be larger and more frequent in industries where changes in market and industry-related fundamentals are larger and more frequent. If so, observed systematic variation might be a useful proxy for (unobserved) firm-specific fundamentals

variation. We therefore tentatively interpret absolute systematic return variation, $\ln(\sigma_m^2)$, as a proxy for firm-specific fundamentals variation, and revisit this issue later.

If this interpretation of $\ln(\sigma_m^2)$ is valid, using relative, rather than absolute, firm-specific return variation is an alternative way of controlling for firm-specific fundamentals variation. Since relative firm-specific return variation, ψ , is the difference between $\ln(\sigma_\varepsilon^2)$ and $\ln(\sigma_m^2)$, using ψ as the independent variable is equivalent to using $\ln(\sigma_\varepsilon^2)$ as the independent variable and constraining the coefficient of $\ln(\sigma_m^2)$ to be the inverse of the coefficient of $\ln(\sigma_\varepsilon^2)$. We therefore include $\ln(\sigma_m^2)$ as a control variable in regressions of absolute firm-specific return variation, but not in regressions of relative firm-specific return variation.

We can also estimate fundamentals variation directly. Following Morck, Yeung, and Yu (2000), we construct variables analogous to our stock return variation measures $\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, and Ψ , but using the annual return on assets (ROA) instead of stock returns. We define ROA as net income plus depreciation plus interest, all divided by tangible assets. The denominator is described in Appendix equation [A5].

To estimate firm-specific fundamentals variation for each industry, we run regressions of the form of [1], but using ROA rather than stock returns. That is, we run

$$ROA_{i,j,t} = \beta_{j,0} + \beta_{j,m}ROA_{m,t} + \beta_{j,i}ROA_{i,t} + \varepsilon_{i,j,t} \quad [13]$$

for each firm j in each industry i , with t an annual time index. The dependent variable, $ROA_{i,j,t}$ is firm j 's ROA, $ROA_{m,t}$ is a value-weighted market average ROA, and $ROA_{i,t}$ is a value-weighted industry average ROA. Again, we exclude the firm in question from these averages. We run these regressions on our 1983-to-1992 sample of nonfinancial firms, described in the Appendix. We drop firms for which fewer than six years of data are available.

We follow the same step-by-step procedure outlined above with regards to [1] through [5].

This variance decomposition lets us express an industry-average ${}_{ROA}R^2$ as

$${}_{ROA}R_i^2 = \frac{{}_{ROA}\sigma_{m,i}^2}{{}_{ROA}\sigma_{\varepsilon,i}^2 + {}_{ROA}\sigma_{m,i}^2}, \quad [14]$$

where

$$\begin{aligned} {}_{ROA}\sigma_{\varepsilon,j}^2 &= \frac{\sum_{j \in i} SSR_{i,j}}{\sum_{j \in i} T_j} \\ {}_{ROA}\sigma_{m,j}^2 &= \frac{\sum_{j \in i} SSM_{i,j}}{\sum_{j \in i} T_j}, \end{aligned} \quad [15]$$

with $SSR_{i,j}$ and $SSM_{i,j}$ now the unexplained and explained variations, respectively, of regression [13] for firm j in industry i . The sum of $SSR_{i,j}$ and of $SSM_{i,j}$ for industry i is scaled by the number of annual return observations $\sum_{j \in i} T_j$.

We again apply logarithmic transformations to obtain our *absolute firm-specific fundamentals variation* measure, $\ln({}_{ROA}\sigma_{\varepsilon,i}^2)$, our *absolute systematic fundamentals variation* measure, $\ln({}_{ROA}\sigma_{m,i}^2)$, and our *relative firm-specific fundamentals variation* measure

$${}_{ROA}\Psi_i = \ln\left(\frac{1 - {}_{ROA}R_i^2}{{}_{ROA}R_i^2}\right) = \ln({}_{ROA}\sigma_{\varepsilon,i}^2) - \ln({}_{ROA}\sigma_{m,i}^2). \quad [16]$$

Note that we again follow Roll (1988) in distinguishing firm-specific variation from the sum of market-related and industry-related variation, and we refer to the latter sum as systematic variation.

Since we have at most ten annual observations per firm, our variance decomposition may be imprecise. Using more years reduces the number of usable firms in each industry, and risks making the fundamentals variation measures reflect conditions that no longer prevail.

Univariate statistics for these control variables are presented in Panel C of Table II, and their correlations with our capital budgeting quality measures are presented in the bottom panel of Table IIIa. Table IIIb presents the correlations of the control variables with each other, with the marginal q and the deviations of \dot{q} from one. The absolute value deviation of \dot{q} from one is negatively correlated with industry size and positively correlated with industry concentration. Both correlations are highly significant (the p -values are 0.00). With these two exceptions, our capital budgeting quality variables are uncorrelated with our control variables.

This suggests that the simple correlation coefficients described above may in fact be meaningful as tests of our hypotheses. However, even though they are individually insignificantly correlated with capital budgeting quality, our control variables may be jointly significant in multiple regressions, to which we now turn.

IV. Regression Results

A. Main results

Table IV presents regressions of the distance of marginal q from one on firm-specific stock price variation and the controls. The central result is that higher firm-specific stock return variation is statistically significantly associated with marginal q nearer one. This is true whether we measure distance from one as absolute deviation, $|\dot{q}-1|$, or squared deviation, $(\dot{q}-1)^2$. It is also true whether we measure firm-specific return variation as absolute variation, $\ln(\sigma_\varepsilon^2)$, or as relative variation, Ψ_i , and regardless of whether the controls are included or not. The regression using relative firm-specific variation is weaker though. The coefficient of interest in regression 4.8 of Table IV attains a nine percent probability level, while that in regression 4.4 of Table IV only achieves eleven percent.

[Table IV here]

Table IV ignores taxes and other complications that can bias \hat{q} and thus push h , the optimal \hat{q} , away from one. When we consider the ways in which taxes and other factors can raise or lower both \hat{q} and thus h , we note that these factors most likely affect our \hat{q} estimates uniformly, or at least randomly. Consequently, our estimated distances between \hat{q} and the similarly distorted optimum, h , may also be distorted uniformly, or at least randomly, and thus can still be used as an inverse indicator of capital budgeting quality.

Table V therefore allows the \hat{q} threshold value, h , to be estimated endogenously following the non-linear procedure reported in Appendix II. Depending on the specification, h ranges from 0.715 to 0.908, and the Wald tests show it to differ significantly from one in all regressions save regression 5.8 of Table V. The regression coefficients are similar to those reported in Table IV, but have somewhat higher statistical significance.

[Table V here]

Overall, these findings are consistent with the conjecture that greater firm-specific stock return variation is associated with higher quality capital budgeting.

B. Robustness

A battery of robustness checks generates qualitatively similar results to those presented above; that is, an identical pattern of signs and statistical significance arises across all of the checks. Space constraints limit us to a brief synopsis.

Although we use Newey-West heteroskedasticity-consistent standard errors, outliers could still affect our findings. Hadi's (1992, 1994) method (cut-off = 0.05) does not reveal outlier problems. Dropping observations for which the Cook's D is greater than one or even 0.5 does not change our findings, nor does dropping the top and bottom five percent of observations of all our main variables.

We can estimate marginal q in a variety of ways. First, we modify [9], [10], and [11] to include R&D and advertising as capital expenditure in the estimation of \dot{q} .⁹ Second, [A7] estimates fixed assets recursively assuming ten percent economic depreciation. An alternative approach uses accounting depreciation, as in [A13]. Third, we estimate \dot{q} as the marginal change in shareholder value instead of firm (equity plus debt) value. Finally, we estimate industry \dot{q} including fixed firm effects, so each firm has its own expected asset growth rate net of depreciation, α^i in [11]. Qualitatively similar results to those in the tables arise in each case.

We estimate σ_ε^2 in [1], [2], and [3] using daily data. Some listed firms may be thinly traded. Non-trading generates zero returns, and a string of zero returns can artificially raise our estimated σ_ε^2 . To mitigate this problem, we also use weekly, bi-weekly, and monthly data. All three procedures generate qualitatively similar results to those reported in Tables IV and V.

We consider alternative constructs for our basic control. First, using Herfindahl indexes based on assets or employees, rather than sales, generates similar results. So does controlling for industry size using the logarithms of 1990-to-1992 average book assets or employees, or using fixed capital estimated recursively from reported depreciation, rather than a ten percent depreciation rate. Controlling for liquidity using cash flow over assets and past external financing (described in Appendix I.c), rather than net current assets over tangible assets as in [A9], also yields comparable results. So does including all three liquidity measures. Finally, we can substitute variants of our basic fundamentals co-movement variables. For example, we use [A7] to adjust the denominator of ROA for inflation, construct ROA entirely from book values, or adjust PP&E with reported depreciation, as in [A13]. All these procedures generate qualitatively similar results to those shown, as do a host of other variants.¹⁰

Another concern is that we miss important industry characteristics. First, rapidly growing industries, such as high-tech, might exhibit a variety of attributes that bias our \dot{q} estimates. Although lagged average q and spending on intangibles already control for such industries, we can also include current average q and past stock returns. We also repeat our regressions using only industries that report zero R&D. Second, because an industry's exposure to foreign trade might affect the quality of capital budgeting, we include industry exports minus imports over sales and industry capital-labor ratios.¹¹ Third, firm size might be as important as industry size. Hence, we add *average* firm size in each industry: the logarithms of 1990-to-1992 average book assets, real sales, employees, or PP&E - estimated using either [A7] or [A13]. Fourth, regulated utilities (SIC 4900 through 4999) may be subject to different constraints than unregulated firms despite the liberalization in the 1980s. We therefore drop these industries. All these variations generate results qualitatively similar to those shown.

We can also ignore statistical propriety and change our empirical specification.

First, instead of using 1990-to-1992 return variation and 1993-to-1997 marginal q 's, we can use contemporaneous data from either period. This yields results qualitatively similar to those shown.

Second, we split our sample by \dot{q} . In high- \dot{q} subsamples ($\dot{q} > 1.0, 0.9, 0.8,$ or 0.7), regressions analogous to those in Table IV, but explaining \dot{q} , have negative significant coefficients on both $\ln(\sigma_\varepsilon^2)$ and Ψ . For low- \dot{q} subsamples ($\dot{q} < 1.0, 0.9, 0.8,$ or 0.7), these coefficients are positive and significant. The finding that \dot{q} rises with firm-specific return variation in low- \dot{q} subsamples, but falls with firm-specific variation in the high- \dot{q} subsamples, makes it improbable that our results are artifacts of either liquidity constraints or inframarginal projects.

In conclusion, our results survive a battery of robustness checks. While we acknowledge that further analysis may overturn these results, we believe we have presented persuasive evidence that greater firm-specific stock return variation is associated with marginal q ratios better aligned to value maximization.

C. Economic Significance

Our results are highly economically significant. In regression 4.7, a one standard deviation increase in absolute firm-specific stock return variation, $\ln(\sigma_e^2)$, reduces $|\dot{q} - 1|$ by 0.239×0.807 or 0.193, roughly 34 percent of the absolute distance of marginal q from one across industries. A one standard deviation increase in relative firm-specific stock return variation, Ψ , reduces the absolute distances of marginal q from one by 14 percent. The improvements, when measured by the squared distances of marginal q from one, are 28 percent and 13 percent, respectively.

V. Discussion

Our results show capital budgeting to be more aligned with market value maximization in industries where firm-specific return variation is higher. Our preferred interpretation of these findings extends the French and Roll (1986) and Roll (1988) contention that firm-specific variation reflects the intensity of informed trading with the additional contention that more intense is informed trading, the closer share prices are to fundamentals. We feel this is the simplest interpretation of our findings, and therefore the preferred interpretation by Ockham's razor.

In this section, we weigh alternative interpretations and possible underlying economic implications of, and explanations for, our preferred interpretation.

A. The Information Content of Stock Prices

Roll (1988) finds that firm-specific return variation is largely unrelated to public

announcements, and contends that it reflects the capitalization of private information into share prices *via* informed trading. However, he concedes (p. 56) that it might also reflect “occasional frenzy unrelated to concrete information.” We argued above that other research makes the latter interpretation unlikely. We now consider the plausibility of this interpretation in the context of our results.

First, greater error in stock prices should cause our \hat{q} estimates to deviate more from their “true” value as assessed by investors. This, *ceteris paribus*, would raise the likelihood of finding a positive correlation (not the observed negative one) between firm-specific return variation and the distance of \hat{q} from h .

Second, more error-laden share prices should cause corporate governance mechanisms to misfire, and perhaps to be disarmed. Yet capital investment is more, not less, aligned with market value maximization in higher firm-specific return variation industries. This is consistent with high firm-specific variation indicating large pricing errors only if managers’ decisions are more aligned with shareholder value maximization where share prices are less informed. This seems improbable.

Third, more erroneous stock prices should magnify information asymmetry problems, strengthening liquidity constraints. Yet we find less evidence of capital rationing in high- \hat{q} industries with larger firm-specific return variation.

Of course, we can never exclude alternative explanations absolutely. For example, \hat{q} might be higher where capital spending is less predictable. If higher $\ln(\sigma_\varepsilon^2)$ and Ψ are associated with less predictable capital budgeting in low- \hat{q} industries (where capital budgeting is already highly predictable), but with greater predictability in high- \hat{q} industries (where capital budgeting is already less predictable), our findings could ensue. Alternatively, capital spending might become lumpier as $\ln(\sigma_\varepsilon^2)$ and Ψ rise for low- \hat{q} industries, but less lumpy as $\ln(\sigma_\varepsilon^2)$ and Ψ rise for high- \hat{q} industries.

Or, some interaction of such effects might be devised. While such stories are didactically possible, they are – in our view – improbable.

If our preferred interpretation of our findings is valid, some inferences follow.

First, our preferred interpretation is also consistent with the use of return asynchronicity to measure the intensity of informed trading, as implied by French and Roll (1986) and Roll (1988), and as used by Bushman, Piotroski, and Smith (2002), Morck, Yeung and Yu (2000), and others.

Second, our preferred interpretation is consistent with the use of return asynchronicity as a measure of the functional-form efficiency of the stock market, in the sense of Tobin (1982) and as proposed by Wurgler (2000). Our results suggest that capital allocation is more aligned with shareholder value maximization where share prices are more asynchronous. If shareholder value maximization, in turn, corresponds to economic efficiency, a positive correlation between Ψ and higher return asynchronicity follows.

Third, many industries have estimated \hat{q} well above our estimated h , and so appear to underinvest. Many others have $\hat{q} < h$, and so appear to overinvest. Underinvestment could be due to liquidity constraints arising from information asymmetries, or to managerial risk aversion. Overinvestment could be due to a variety of agency problems, such as Jensen's (1986) free cash flow hypothesis or Roll's (1988) hubris hypothesis, and become more important when share prices are less informed. These deviations of \hat{q} estimates from h suggest that these stories are economically important, and that some are more important than others in specific industries.

This discussion begs the question of how stock prices should track fundamentals more closely in industries whose stocks move less synchronously (i.e., have higher Ψ). Morck, Yeung, and Yu (2000), Wurgler (2000), and Bushman, Piotroski, and Smith (2002) stress differences in institutional

environments across countries. All U.S. firms are presumably subject to the same institutional environment, so cross-industry differences within the U.S. must be due to other factors.

B. Incomplete Arbitrage?

In this section, we speculate about how stock prices might come to track fundamentals more closely in industries with more asynchronous stock returns. We do this very tentatively, as we are uncertain of the validity of these ideas, and we welcome other explanations of our findings.

Grossman and Stiglitz (1980) argue that arbitrage is limited by the cost of obtaining and analyzing the information needed to estimate fundamental values. In addition, they make the point that greater risk aversion of the informed traders will also limit arbitrage and thus price informativeness (p. 399). Shleifer and Vishny (1997) and Shleifer (2000, chapter 4) expand on these ideas. Arbitrageurs' risk aversion matters because arbitrageurs must hold large undiversified portfolios and bear *holding period risk* - the risk that new information will send the price in the wrong direction before the stock price has time to move to the arbitrageur's previously correct estimate of its fundamental value. Information gathering and processing costs and holding period risk matter because arbitrageurs do not gather and process information if their expected return from doing so does not justify the cost and risk.

These considerations raise the possibility that arbitrage might be more severely limited in some industries than in others. We now consider some specific ways in which this might happen.

B.1 The Absence of Firm-specific Arbitrage

First, such differences might arise if the basic business activities of firms in some industries are intrinsically harder for arbitrageurs to predict. If so, arbitrage limits might more severely curtail firm-specific arbitrage plays in those industries. Since French and Roll (1986) and Roll (1988) find firm-specific stock price fluctuations mainly reflect private information being incorporated into prices

by informed trading, an absence of arbitrage on firm-specific information might be associated with depressed firm-specific return variation – at least over short intervals.

Over long intervals, the cost of firm-specific information about different firms might rise and fall exogenously. In this case, informed arbitrage on each stock would happen when firm-specific information about that stock is cheap. If we observe stocks for longer time intervals, differences in the extent of informed trading should wash out. Even if information about some firms is always more costly than information about other firms, a longer interval might mitigate differences in the extent of informed trading. This is because a steadily increasing divergence of the firm-specific component of a stock return from its fundamental value should eventually induce arbitrage, and a consequent discrete jump as the price finally moves to its fundamental value. That is, uncapitalized firm-specific information is “built up and discharged.” This *capacitance theory of information* capitalization implies that differences in firm-specific return variation should fade if we measure them over sufficiently long intervals. We use a three-year window to estimate $\ln(\sigma_\varepsilon^2)$ and Ψ . As we extend our estimation window, the differences across industries decrease and their statistical significance of these variables in the regressions falls, though their signs do not change. A ten-year window is sufficient to render all the coefficients statistically insignificant.

Unfortunately, this might also merely reflect a greater use of stale data, and so cannot be taken as clear confirmation of this explanation. We are pursuing this in a subsequent paper.

However, a lack of firm-specific arbitrage might not lead to a steadily increasing divergence of the share price from its fundamental value if the firm-specific component of fundamental value is mean reverting. This might occur if firm-specific differences in returns are due to firm-specific corporate governance problems, which are corrected over the longer term, or to exceptional firm-specific corporate governance, which does not last. If old firm-specific information grows stale, or

depreciates, in this way, an absence of informed trading might not cause an uncanceled information build-up. This *depreciation theory of information* means the gap between true value and market value need not grow with elapsed time and need not eventually trigger arbitrage. Some firm-specific events might pass into irrelevance without ever being capitalized into share prices.

If this hypothesis underlies our results, we might expect the firm-specific component of earnings to exhibit more mean reversion than industry or market-wide earnings averages. We are pursuing this possibility in a subsequent paper.

B.2 Agency Problems and Firm-specific Arbitrage

A second, closely related possibility is that management might more readily appropriate cash flows in some industries than in others. If management appropriates abnormally high cash flows due to abnormally high market-wide or industry-wide earnings, this is obvious to shareholders unless all the managers of other firms do likewise. However, if management appropriates abnormally high firm-specific cash flows, shareholders may never know. Arbitrageurs, however, might come to rationally expect such appropriations, and thus view predicting firm-specific fundamentals changes as of little value. If so, firm-specific return variation would be depressed.

If insiders' misappropriation raises operating costs, we should see a corresponding effect on firm-specific fundamentals variation, ${}_{ROA}\sigma_{\varepsilon}^2$. However, if insiders' pilfering unlinks earnings from dividends, earnings variation might be unaffected. This effect, however, might be distinguishable as a negative skewness in the firm-specific components of individual stock returns, for insiders would tend to appropriate positive firm-specific return, but not negative ones. We are pursuing this possibility elsewhere.

B.3 Noise Traders and Firm-specific Arbitrage

A third possibility is that noise traders concentrate their trading in certain “fad” industries. Black (1986) shows that noise traders are required for the stock market to function. De Long et al. (1990) show that noise trader induced stock price movements need not immediately be dampened by arbitrageurs, and they argue that this is especially likely when noise traders’ mispricing errors are systematic. They consequently propose that noise trading induces market-wide return variation unrelated to fundamentals – which we would observe as an elevated $\ln(\sigma_m^2)$ and a depressed Ψ . This noise trader induced systematic variation increases the holding period risk that arbitrageurs must bear, and this deters arbitrage, lowering our measured $\ln(\sigma_\epsilon^2)$ and Ψ .

However, this interpretation would seem inconsistent both with the typical insignificance of systematic variation, $\ln(\sigma_m^2)$, in our results, and with firm-specific relative to systematic variation, Ψ_i , not working as well as absolute firm-specific variation, $\ln(\sigma_\epsilon^2)$, in some of the our regressions. Nonetheless, our incomplete understanding of the real importance and nature of noise trading prevents a categorical rejection of this hypothesis at present.

B.4 Qualification

The idea that different stock prices might track their fundamental values with different degrees of precision underlies our interpretation of our empirical findings. If valid, this notion itself is potentially quite important. We recognize that extensive further empirical investigation is needed to fully ascertain its validity, and to deduce the nature of the information economics that must underlie it. Moreover, we recognize that our interpretation of our finding may be erroneous. Consequently, we welcome other explanations of our empirical finding that industries in which stock returns are less synchronous have marginal q ratios closer to its optimal value.

VI. Conclusions

Our main conclusion is capital budgeting seems more closely aligned with market value maximization in industries whose stocks exhibit greater firm-specific return variation. That is, we find fewer marginal q ratios far above or far below a theoretical optimum in industries exhibiting higher firm-specific stock return variation. This finding is highly statistically and economically significant. It is also robust and survives controlling for firm-specific fundamentals variation and other factors that might affect stock return synchronicity.

This is of interest for several reasons.

First, Roll (1988) attributes the low R^2 statistics common in asset pricing models to high firm-specific return variation, and this firm-specific variation is not associated with public information releases. He concludes (p. 56) that it rather reflects “either private information or else occasional frenzy unrelated to concrete information.” Our preferred interpretation of our findings is inconsistent with firm-specific return variation reflecting investor frenzy. Indeed, our findings imply that firm-specific return variation is due to informed trading, and that share prices are actually closer to fundamental values where firm-specific return variation is higher! One possibility is that activity by informed traders reduces noise trader induced errors in share prices, as in De Long et al. (1990).

Second, the extent to which corporate capital budgeting decisions maximize market value is a crucial issue in finance. Managers may make capital budgeting decisions that do not maximize market value because of corporate governance problems associated with managerial self-interest, ignorance, or incompetence. Sub-optimal capital budgeting decisions can also result from costly external financing (due to information asymmetry between managers and investors) or other sorts of liquidity constraints. If our interpretation of our results is correct, firms follow capital budgeting policies more aligned with market value maximization where stock prices are more informed.

Third, our interpretation of our results raises the possibility that stock prices track fundamental values with differing degrees of accuracy in different industries. That is, rather than being “efficient” or “inefficient,” the stock market exhibits a range of efficiency levels in different industries. How could this be? We speculate that such differences might arise because arbitrage is complete to different degrees across industries. But this begs the question of what determines the completeness of arbitrage. We speculate about possible roles for differences in transparency, arbitrage costs, arbitrage risks, monitoring costs, agency problems, and noise trading activity. Our findings suggest that a better understanding of what determines the limits to arbitrage is of fundamental importance.

Fourth, if we follow Tobin (1982) and define the stock market as *functional-form efficient* if stock price movements bring about economically efficient capital budgeting, our results suggest stock prices are more functionally efficient where firm-specific return variation is larger. This *functional form of the efficient markets hypothesis* is important because the quality of corporate capital allocation decisions has major ramifications for the real economy.

Finally, although we believe this interpretation of our finding is sound, we recognize that this work is preliminary and we welcome other explanations of our finding that greater firm-specific return variation coincides with marginal Tobin’s q ratios closer to optimal values.

Appendix

I.a Construction of the Datasets

Our sample begins with all companies listed in the WRDS CRSP/COMPUSTAT Merged Database from 1990 to 1992. We discard duplicate entries for preferred stock, class B stock, and the like by deleting entries whose CRSP CUSIP identifiers append a number other than 10 or 11. Since accounting data for financial and banking firms (SIC codes from 6000 through 6999) are not comparable, we exclude them.

Since the analysis below requires more than one firm in each industry in constructing the firm-specific stock return variables, we drop industries that contain fewer than three firms. We also drop firm-year observations with fewer than thirty days of daily stock return data. When firms are delisted and COMPUSTAT indicates that a bankruptcy occurred, we assume a final daily return of minus 100 percent. When firms are delisted and COMPUSTAT indicates that a corporate control event occurred the final return is taken as given.

After these procedures, our final “1990 to 1992 sample” contains 4,066 firms spanning 205 three-digit SIC industries. We use this sample to construct our firm-specific stock return variation variables and most of our control variables.

Constructing some control variables requires a longer panel, starting prior to 1993. For these, we expand the 1990-to-1992 sample backward to 1983 by retaining sample firms that remain listed in COMPUSTAT in the period demarcated by those years. This “1983-to-1992 sample” contains 4,747 firms spanning 204 industries.

We use data from a “1993-to-1997 sample” to construct our capital budgeting quality variables. This sample consists of all firms listed in COMPUSTAT during those years in the industries spanned by our 1990-to-1992 sample. Our final 1993-to-1997 sample contains 16,782

firm-year observations spanning 199 three-digit industries. (The length of this window is arbitrary; our results hold if we use a shorter data window, e.g., 1993 to 1995.)

When COMPUSTAT reports a value as “insignificant”, we set it to zero. When companies change their fiscal years, COMPUSTAT records one fiscal year with fewer than twelve months and another with more than twelve months. Under some circumstances, this causes COMPUSTAT to report a missing year observation. If a firm’s fiscal year ends before June 15th, COMPUSTAT reports it as data for the previous year on the grounds that more than half of the fiscal year occurred in the previous calendar year. This convention causes missing values if no fiscal year has the majority of its months in the calendar year of the change. We drop such firms.

In all three samples, we define *industries* as sets of firms that share the same primary three-digit SIC code in the COMPUSTAT Business Segment file. Firms need not have data for all time periods to be included in any of the samples. Hence, ours samples are all unbalanced panels.

I.b. Marginal Tobin’s q Estimation Procedure

We define marginal q as the unexpected change in firm value during period t divided by the unexpected increase in capital goods during period t . We write this as

$$\dot{q}_j = \frac{V_{j,t} - E_{t-1}V_{j,t}}{A_{j,t} - E_{t-1}A_{j,t}} = \frac{V_{j,t} - V_{j,t-1}(1 + \hat{r}_{j,t} - \hat{d}_{j,t})}{A_{j,t} - A_{j,t-1}(1 + \hat{g}_{j,t} - \hat{\delta}_{j,t})} \quad [\text{A1}]$$

where $\hat{r}_{j,t}$ is the expected return from owning the firm, $\hat{d}_{j,t}$ is the firm’s expected disbursement rate (including cash dividends, share repurchases, and interest expensive), $\hat{g}_{j,t}$ is the expected rate of spending on capital goods, and $\hat{\delta}_{j,t}$ is the expected depreciation rate on those capital goods.

Rewriting [A1], normalizing by $A_{j,t-1}$, we obtain

$$V_{j,t} - V_{j,t-1} = \dot{q}_j [A_{j,t} - A_{j,t-1}(1 + g_{j,t} - \delta_{j,t})] + V_{j,t-1}(\hat{r}_{j,t} - \hat{d}_{j,t}), \quad [\text{A2}]$$

or

$$\frac{V_{j,t} - V_{j,t-1}}{A_{j,t-1}} = -\dot{q}_j (g_j - \delta_j) + \dot{q}_j \frac{A_{j,t} - A_{j,t-1}}{A_{j,t-1}} - \xi_j \frac{div_{j,t-1}}{A_{j,t-1}} + r_j \frac{V_{j,t-1}}{A_{j,t-1}}, \quad [\text{A3}]$$

where $div_{j,t-1}$ is dollar disbursements.

Note that the intercept in [A3] is an estimate of $-\dot{q}_j (g_j - \delta_j)$, where the j subscript indicates a time average. The coefficients of lagged disbursements and lagged *average q* can be loosely interpreted as a tax correction factor and an estimate of the firm's weighted-average cost of capital.

We estimate $V_{j,t}$ and $A_{j,t}$ as

$$V_{j,t} = P_t (CS_{j,t} + PS_{j,t} + LTD_{j,t} + SD_{j,t} - STA_{j,t}), \text{ where} \quad [\text{A4}]$$

$$A_{j,t} \equiv K_{j,t} + INV_{j,t}, \quad [\text{A5}]$$

$CS_{j,t}$ = the end of fiscal year- t market value of the outstanding common shares of firm j ,

$PS_{j,t}$ = the estimated market value of preferred shares (the preferred dividends paid over the Moody's baa preferred dividend yield),

$LTD_{j,t}$ = estimated market value of long-term debt,

$SD_{j,t}$ = book value of short-term debt,

$STA_{j,t}$ = book value of short-term assets,

P_t = inflation adjustment using the GDP deflator,

$K_{j,t}$ = estimated market value of firm j 's PP&E, and

INV = estimated market value of inventories.

Before continuing, we provide details on the estimation of the market values of long-term debt, PP&E, and inventories.

We estimate the market value of long-term debt recursively. We construct a fifteen-year age profile of each firm's debt each year based on changes in book values. We estimate the market value

of each vintage of each firm's debt in each year assuming all bonds to be fifteen-year coupon bonds issued at par. We use Moody's *Baa* bond rates to proxy for all bond yields.

We use a recursive algorithm to estimate the value of PP&E, $K_{j,t}$. This is necessary because historical cost accounting makes simple deflators questionable in adjusting for inflation. We begin by converting all figures to 1983 dollars. We assume that physical assets depreciate by ten percent per year. Let $K_{j,t-10}$ be the book value of net PP&E (in 1983 dollars) for firm j in year t . (If a company's history is shorter than ten years, we start the rolling equation with the first year available.) Accordingly, PP&E in year $t-9$ is then

$$K_{j,t-9} = (1 - \delta) K_{j,t-10} + \frac{\Delta X_{j,t-9}}{1 + \pi_{t-9}}. \quad [\text{A6}]$$

More generally, we apply the recursive equation

$$K_{j,t+1} = (1 - \delta) K_{j,t} + \frac{\Delta X_{j,t+1}}{\prod_{\tau=0}^{t+1} (1 + \pi_{\tau})}. \quad [\text{A7}]$$

Thus, PP&E in year $t + 1$ is PP&E from year t minus ten percent depreciation plus current capital spending, denoted $\Delta X_{j,t+1}$, deflated to 1983 dollars using π_t , the fractional change in the seasonally adjusted producer price index for finished goods published by the U.S. Department of Labor, Bureau of Labor Statistics.¹²

A similar recursive process is sometimes necessary to estimate the market value of inventories. The market value is taken as equal to the book value for firms using FIFO accounting. For firms using LIFO accounting, a recursive process analogous to that described in [A7] is used to estimate the age structure of inventories. Inventories of each age cohort are then adjusted for inflation using the GDP deflator.

We partition the 1993-to-1997 sample into three-digit industry subsamples of firms. For each subsample, we regress

$$\frac{\Delta V_{j,t}^i}{A_{j,t-1}^i} = \alpha^i + \beta_0^i \frac{\Delta A_{j,t}^i}{A_{j,t-1}^i} + \beta_1^i \frac{V_{j,t-1}^i}{A_{j,t-1}^i} + \beta_2^i \frac{D_{j,t-1}^i}{A_{j,t-1}^i} + u_{j,t}^i \quad [\text{A8}]$$

to obtain a marginal q estimate, $\hat{q}_i \cong \beta_0^i$, for that industry; $D_{j,t-1}^i$ is defined as dividends for common shares plus repurchases of common shares plus interest expenses.

Error terms are assumed to satisfy the following conditions: $u_{j,t}^i$ has zero mean, $\text{cov}(u_{j,t}^i, u_{j,s}^i) \neq 0 \forall t$ and s ; and, $\text{cov}(u_{j,t}^i, u_{k,t}^i) \neq 0 \forall j$ and k . Equation [16] is estimated using the GLS method. All variables are scaled by $A_{j,t-1}^i$ to mitigate heteroskedasticity problems.

To mitigate the effect of outliers we drop companies with tangible assets less than one million dollars and with absolute growth rates in tangible assets and value (scaled by tangible assets) greater than 300 percent. Dropping companies with absolute values of growth rates greater than 200 percent, 100 percent or not dropping them at all does not change our results. We require at least ten firm-year observations to estimate [A8]. Finally, we omit two industries from our analysis for which the marginal q takes extremely high values of 4.79 and 6.88. Keeping them in our sample does not change the results.

The intersection of the “1983 to 1992,” “1990 to 1992,” and “1993 to 1997” samples results in the final sample of 196 three-digit industries we use in our analysis.

I.c Additional Variables

Our basic liquidity measure is net current assets as a fraction of total assets

$$\hat{\lambda}_i = \frac{\sum_{j \in i, t \in [1990, 1992]} \text{current assets}_{j,t} - \text{current liabilities}_{j,t}}{\sum_{j \in i, t \in [1990, 1992]} \text{tangible assets}_{j,t}} \quad [\text{A9}]$$

for each industry i for the years from 1990 through 1992, where firm j is in industry i . The denominator is real PP&E, estimated using the recursive procedure in [17], plus real inventories.

We define *cash flow over total assets* as

$$c_i = \frac{\sum_{j \in i, t \in [1990, 1992]} \text{income}_{i,j,t} + \text{depreciation}_{i,j,t}}{\sum_{j \in i, t \in [1990, 1992]} \text{tangible assets}_{i,j,t}}, \quad [\text{A10}]$$

where j is an index over firms that are members of industry i . The numerator is constructed by summing inflation-adjusted 1990, 1991, and 1992 data for all firms in each industry. The denominator is industry real PP&E, estimated using the recursive procedure in [A7], plus real inventory.

We define *past long-term debt* as

$$ltd_i = \max \left[0, \min \left[\frac{\sum_{j \in i, t \in [1990, 1992]} \Delta LD_{j,t}}{\sum_{j \in i, t \in [1990, 1992]} \Delta X_{j,t}}, 1 \right] \right], \quad [\text{A11}]$$

where $\Delta LD_{j,t}$ is the book value of net long-term debt issued by firm j in industry i during year $t \in [1990, 1992]$, as reported in COMPUSTAT. The total value of capital spending by firm j in industry i in year $t \in [1990, 1992]$ is $\Delta X_{j,t}$. This variable is bounded within the unit interval.

We analogously define *past outside financing* as

$$d\&e_i = \max \left[0, \min \left[\frac{\sum_{j \in i, t \in [1990, 1992]} (\Delta LD_{j,t} + \Delta SD_{j,t} + \Delta E_{j,t})}{\sum_{j \in i, t \in [1990, 1992]} \Delta X_{j,t}}, 1 \right] \right] \quad [\text{A12}]$$

where $\Delta LD_{j,t}$ and $\Delta X_{j,t}$ are defined as in A[11], $\Delta SD_{j,t}$ is net new short-term debt and accounts payable from the balance sheets of all firms j in industry i , and $\Delta E_{j,t}$ is net new equity issues by all firms j in industry i , both again from 1990 to 1992. This past outside financing variable is again bounded within the unit interval. In constructing lev_i and $d\&e_i$, we assume new debt or equity to be nil if these variables are not reported in COMPUSTAT but all major financial variables are reported.

As an *alternative estimate of the total value of property, plant and equipment*, we use reported accounting depreciation each year, $DEP_{j,t}$, rather than the assumed ten percent economic depreciation rate used in [A7]. The resulting recursive formula,

$$K_{j,t+1} = K_{j,t} - DEP_{j,t+1} + \frac{\Delta X_{j,t+1}}{\prod_{\tau=0}^{t+1} (1 + \pi_{\tau})}, \quad [\text{A13}]$$

generates an alternative panel of firm-level fixed assets. Using this measure throughout rather than that from [A7] does not qualitatively change our findings.

II. *Nonlinear Estimation in Table V*

Consider a specification with dependent variable the squared deviation of marginal q from h ,

$$(\dot{q}_i - h)^2 = b_{\varepsilon} \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i + u_i.$$

This is equivalent to

$$\dot{q}_i^2 = -h^2 + 2h\dot{q}_i + b_{\varepsilon} \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i + u_i.$$

Our aim is to estimate the vector of parameters $\mathbf{b} = \{h, b_{\varepsilon}, b_m, \mathbf{c}'\}$ using nonlinear least squares (NLS). In NLS, the following criterion function is minimized with respect to \mathbf{b} :

$$Q_i(\mathbf{b}) = \frac{1}{I} [\mathbf{y} - \mathbf{f}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_I; \mathbf{b})]' [\mathbf{y} - \mathbf{f}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_I; \mathbf{b})] = \frac{1}{I} \sum_{i=1}^I [y_i - f(\mathbf{x}_i; \mathbf{b})]^2, \quad [\text{A16}]$$

where $y_i = \dot{q}_i^2$ and $f(\mathbf{x}_i, \mathbf{b}) = -h^2 + 2h\dot{q}_i + b_{\varepsilon} \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i$. The NLS estimates are computed numerically using the Gauss-Newton algorithm.

Similarly, when the dependent variable is the absolute deviation of the marginal q from one,

$$|\dot{q}_i - h| = b_{\varepsilon} \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i + u_i$$

is equivalent to

$$\dot{q}_i^2 = -h^2 + 2h\dot{q}_i + \left(b_\varepsilon \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \cdot \mathbf{Z}_i + u_i \right)^2$$

because $(|x|)^2 = x^2$. In this case we estimate $y_i = f(\mathbf{x}_i; \mathbf{b}) + \varepsilon_i$ where $y_i = \dot{q}_i^2$ and

$$f(x_i, \mathbf{b}) = -h^2 + 2h\dot{q}_i + \left(b_\varepsilon \ln(\sigma_{\varepsilon,i}^2) + b_m \ln(\sigma_{m,i}^2) + \mathbf{c}' \mathbf{Z}_i \right)^2.$$

Other specifications in Table V and in the robustness checks section are estimated analogously.

References

- Amemiya, T., 1985, *Advanced Econometrics* (Harvard University Press, Cambridge, MA).
- Amihud, Yakov, and Baruch Lev, 1981, Risk reductions as a managerial motive for conglomerate mergers, *Bell Journal of Economics* 12, 605-617.
- Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529-543.
- Bushman, R., J. Piotroski, and A. Smith, 2002, What determines corporate transparency?, working paper, University of North Carolina.
- Collins, Daniel W., S. P. Kothari, and Judy Rayburn, 1987, Firm size and the information content of prices with respect to earnings, *Journal of Accounting and Economics* 9, 111-138.
- De Long, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert J. H. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.
- Durnev, Artyom, Randall Morck, Bernard Yeung, and Paul Zarowin, 2001, Does greater firm-specific return variation mean more or less informed stock pricing?, working paper, New York University.
- French, Kenneth R., and Richard Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17, 5-26.
- Grossman, Sanford, and Joseph Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.
- Hadi, A.S., 1992, Identifying multiple outliers in multivariate data, *Journal of the Royal Statistical Society Series B* 54, 761-771.
- Hadi, A.S., 1994, A Modification of a method for the detection of outliers in multivariate samples, *Journal of the Royal Statistical Society Series B* 56, 393-396.

- Jensen, M., 1986, Agency costs of free cash flows, corporate finance and takeovers, *American Economic Review* 76, 323-329.
- Khorana, Ajay, and Marc Zenner, 1998, Executive compensation of large acquirers in the 1980s, *Journal of Corporate Finance* 4, 209-240.
- Lewellen, Wilbur G., 1971, A pure financial rationale for the conglomerate merger, *Journal of Finance* 26, 521-545.
- Matsusaka, John G., and Vikram Nanda, 1994, Internal capital markets and corporate refocusing, *Journal of Financial Intermediation* 11, 176-211.
- May, Don O., 1995, Do managerial motives influence firm risk reduction strategies?, *Journal of Finance* 50, 1291-1308.
- Morck, Randall, Andrei Shleifer, and Robert W. Vishny, 1990, Do managerial objectives drive bad acquisitions?, *Journal of Finance* 45, 31-48.
- Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215-238.
- Myers, Stewart C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics* 5, 147-175.
- Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *Journal of Finance* 55, 35-80.
- Roll, Richard, 1986, The hubris hypothesis of corporate takeovers, *Journal of Business* 59, 197-216.
- Roll, Richard, 1988, R^2 , *Journal of Finance* 43, 541-566.
- Shiller, Robert, 1989, Comovements in stock prices and comovements in dividends, *Journal of Finance* 44, 719-30.

- Scharfstein, David S., and Jeremy C. Stein, 2000, The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *Journal of Finance* 55, 2537-2564.
- Shleifer, Andrei, 2000, *Inefficient Markets: An Introduction to Behavioral Finance - Clarendon Lectures in Economics* (Oxford University Press, London, U.K.).
- Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.
- Stein, Jeremy C., 1997, Internal capital markets and the competition for corporate resources, *Journal of Finance* 52, 111-133.
- Stein, Jeremy C., 2001, Agency, information and corporate investment, NBER working paper No. W8342. Forthcoming in George Constantinides, Milt Harris and René Stulz, ed.: *Handbook of the Economics of Finance* (North-Holland, Amsterdam).
- Theil, Henri, 1971, *Principles of Econometrics* (Wiley, New York).
- Tobin, James, 1982, On the Efficiency of the Financial System, *Lloyd's Banking Review* 153, 1-15.
- Wurgler, Jeffrey, 2000, Financial markets and the allocation of capital, *Journal of Financial Economics* 58, 187-214.

Footnotes

¹ In our sample, examples of high firm-specific stock return variation industries include: “Apparel, Piece Goods, And Notions,” “Video Tape Rental,” “Miscellaneous Industrial And Commercial,” “Periodicals: Publishing, Or Publishing And Printing,” and “Miscellaneous Chemical Products.” Examples of low firm-specific stock return variation industries include “Combination Electric And Gas, And Other Utility,” “Automotive Rental And Leasing,” “Paperboard Mills,” “Mailing, Reproduction, Commercial Art,” “Women's, Misses', Children's, and Infants.”

² An alternative approach would be to use equity value only as the numerator of marginal q . This would be consistent with the view that managers maximize shareholder value, rather than firm value, but ignores many legal requirements that managers consider creditors’ interests as well if bankruptcy is a reasonable possibility. Focusing on equity value also highlights the issue of whether managers should maximize the value of existing shareholders’ wealth or that of existing and new shareholders. We assume the latter and also add the value of creditors’ claims in [9], so that our implicit maximand is V_t rather than shareholder value. However, we shall point out later that the alternative approach leads to qualitatively similar results.

³ We can omit interest if debt is assumed to be perpetual so that periodic repayments do not affect the principal. Omitting interest expenses does not affect our results. Since we are calculating the return from owning the entire firm, not from owning a single share, stock repurchases must be included as part of cash payments to investors.

⁴ The firm value is defined as a fiscal year-end number of common shares outstanding (COMPUSTAT, data series #25) times a fiscal year-end common shares price (COMPUSTAT, data series #199).

⁵ The five-lowest marginal q industries are: “Asphalt Paving, Roofing Materials,” “Health Services,” “Chemicals and Allied Products,” “Fabricated Rubber Products,” and “Accounting, Auditing and Bookkeeping Services.” The five-highest marginal q industries are: “Power, Distribution, Special Transformers,” “Pens, Pencils, Other Office Materials,” “Motion Picture Theaters,” “Mailing, Reproduction, Commercial Art,” and “Air Transport, Nonscheduled.”

⁶ Instead of one, we can take the “optimal” \hat{q} to be the mean (0.91) or the median (0.87) of our estimated marginal q . The results for the simple correlations and the graphs that we shall depict in Figures 2 and 3 do not change qualitatively.

⁷ Marginal q is negatively correlated with $(\hat{q}-1)^2$ and $|\hat{q}-1|$ because more than 62 percent of our \hat{q} estimates are less than one.

⁸ Lewellen (1971) proposes that diversification stabilizes earnings, and helps firms access debt financing on better terms, all else equal. Matsusaka and Nanda (1994) and Stein (1997) argue that the head office of a diversified firm can act like a financial intermediary, investing surplus funds from one division with positive NPV projects in another, reducing the need for external funds. Amihud and Lev (1981), Morck, Shleifer, and Vishny (1990), May (1995), and Khorana and Zenner (1998) all propose that managerial utility maximization might explain value-destroying diversification, so more diversified firms might be firms with larger agency problems. Scharfstein and Stein (2000) argue that diversified firms shift income from cash-rich divisions to cash-poor ones out of a sense of “fairness.” Rajan, Servaes, and Zingales (2000) propose that such transfers are due to self-interested divisional managers and weak head offices. Thus, different levels of corporate diversification could conceivably generate a spurious correlation between financing decisions and stock return variation in several ways.

⁹ For consistency, this alternative requires that we also capitalize R&D and advertising spending into the replacement cost of total assets. We assume a 25 percent annual depreciation rate on both types of intangible investments to do this.

¹⁰ Dropping observations where $|ROA_{i,j,t} - ROA_{i,j,t-1}| > 25$ percent to avoid spurs in accounting ROA caused by transitory extraordinary events and tax saving practices. Doing so eliminates 869 firm-year observations from our sample. Leaving these observations in does not qualitatively affect our results. Another straightforward variant is to substitute co-movement in return on equity (ROE), net income plus depreciation all over net worth, for ROA in [14]. Constructing this alternative fundamentals co-movement control variable necessitates dropping four observations where net worth is negative. Using co-movement in ROE to control for fundamentals co-movement yields results similar to those shown in the tables. Also, both ROA and ROE co-movement can be estimated relative to an equal, rather than market value, weighting of the indices. Weightings based on sales, book assets, or book equity also yield qualitatively similar results to those shown in the tables. An issue with all the above direct measures of fundamentals variation is that while they are based on a long window, they are unreliable estimates because of changes in firm conditions and the like. Since our purpose is to estimate how similar fundamentals are among firms, we can use a panel variance of $ROA_{i,j,t}$ using all firms j in each industry i in 1990 to 1992 as an alternative control variable. This also produces qualitatively similar results. Using a time-series average of cross-sectional variances also yields qualitatively similar results.

¹¹ Industries more exposed to intensified international competition may make better capital budgeting decisions. In addition, international competition may have heterogeneous impacts on firm returns. Industry imports and exports are from the NBER-CES Manufacturing Industry Database. These data are available only for manufacturing (SIC codes from 2000 to 3999) industries, so our regressions are

restricted to these industries. Capital-labor ratios are deviations from the economy-wide weighted average.

¹² This index is available at <http://www.stls.frb.org/fred/data/ppi/ppifgs>.

Table I

Definitions of Main Variables

<i>Variable</i>		<i>Definition</i>
Panel A. Firm-specific stock return variation variables		
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	Logarithm of residual sum of squares (scaled by the number of firm-year observations) from regressions of firm return on market and three-digit industry value-weighted indices (constructed excluding own return) run on daily data by three-digit industry from 1990 through 1992.
relative firm-specific stock return variation	Ψ	Logarithm of residual sum of squares minus logarithm of explained sum of squares (both scaled by the number of firm-year observations) from the regressions described above.
Panel B. Quality of capital budgeting variables		
marginal q	\dot{q}	A coefficient in the regression of the change in the market value of a firm (scaled by a lagged value of its stock of capital goods) on an unexpected unit increase in its stock of capital goods (scaled by a lagged value of its stock of capital goods) and controls by 3-digit industry using annual data from 1993 through 1997. Tangible assets are defined in [A5] and are equal to the sum of real property, plant, and equipment estimated using recursive formula in [A7], and real inventory.
Panel C. Control variables		
absolute systematic stock return variation	$\ln(\sigma_m^2)$	Logarithm of explained sum of squares (scaled by the number of firm-year observations) from the regressions described above.
absolute firm-specific fundamentals variation	$\ln({}_{ROA}\sigma_\varepsilon^2)$	Logarithm of residual sum of squares (scaled by the number of firm-year observations) from regressions of firm ROA on market and three-digit industry value-weighted ROA indices (constructed excluding own return) run on annual data by three-digit industry from 1983 through 1992. ROA is equal to the sum of income, interest expenses, and depreciation over tangible assets. Tangible assets are defined as in [A5].
absolute systematic fundamentals variation	$\ln({}_{ROA}\sigma_m^2)$	Logarithm of explained sum of squares (scaled by the number of firm-year observations) from the regressions described above.
relative firm-specific fundamentals variation	${}_{ROA}\Psi$	Logarithm of residual sum of squares minus logarithm of explained sum of squares (both scaled by the number of firm-year observations) from the regressions described above.
average q	\bar{q}	Average q is three-digit industry average from 1990 through 1992. The average q for a given industry in a specified period is the sum of the market values of all firms over the sum of all their replacement costs of tangible assets. The market value and the replacement costs of tangible assets are described in the Appendix.
corporate diversification	$segs$	It is 1990-to-1992 average of total assets weighted-average number of three-digit industries a firm operates in.
Herfindahl index	H	It is 1990-to-1992 average of three-digit industry Herfindahl indices constructed using sales data.
size	$\ln(K)$	Log of the average from 1990 to 1992 of real property, plant, and equipment, estimated using the recursive formula in [A7].
liquidity	λ	The ratio of the difference between current assets and current liabilities to tangible assets from 1990 through 1992. Tangible assets are defined as in [A5].
leverage	lev	It is 1990-to-1992 market value of net long-term debt over tangible assets. Tangible assets are defined as in [A5].
advertising spending	adv	Total, from 1990 through 1992, of inflation adjusted advertising expenditures over tangible assets. Tangible assets are defined as in [A5].
R&D spending	$r\&d$	Total, from 1990 through 1992, of inflation adjusted R&D expenditures over tangible assets. Tangible assets is defined as in [A5].

Table II
Univariate Statistics for Main Variables

This table reports the mean, median, standard deviation, min, and max of main variables. Refer to Table I for variable definitions. The sample is 196 three-digit industries for all variables. The return variation measures, σ_ε^2 , σ_m^2 , R^2 , $\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1990-to-1992 data for a sample of 196 three-digit industries spanned by 4,029 firms. The quality of capital budgeting variables, $(\dot{q}-1)^2$ and $|\dot{q}-1|$, are constructed using 1993-to-1997 data for 196 three-digit industries spanned by 16,735 firm-year observations. The controls, \bar{q} , seg , H , $\ln(K)$, λ , lev , adv , and $r\&d$, are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The fundamentals variation controls, $\ln(\sigma_{ROA, \varepsilon}^2)$, $\ln(\sigma_{ROA, m}^2)$, and ${}_{ROA}\Psi$, are constructed using 1983-to-1992 data for 196 three-digit industries spanned by 4,705 firms. To utilize as much information as possible to capture fundamental comovements, we include firms that might not last throughout the period, but had at least six years of continuous data. Finance industries (SIC code 6000 - 6999) are omitted.

<i>Variable</i>		<i>mean</i>	<i>median</i>	<i>standard deviation</i>	<i>minimum</i>	<i>maximum</i>
Panel A. Stock return variation variables						
firm-specific stock return variation	σ_ε^2	0.029	0.024	0.025	0.001	0.154
systematic stock return variation	σ_m^2	0.007	0.006	0.007	0.001	0.056
systematic rel. to firm-specific stock return variation	R^2	0.219	0.206	0.087	0.040	0.560
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	-3.826	-3.731	0.807	-6.775	-1.873
absolute systematic stock return variation	$\ln(\sigma_m^2)$	-5.169	-5.153	0.728	-7.265	-2.875
relative firm-specific stock return variation	Ψ	1.343	1.347	0.523	-0.242	3.170
Panel B. Quality of capital budgeting variables						
marginal q	\dot{q}	0.907	0.867	0.872	-3.333	3.886
squared deviation of marginal q from one	$(\dot{q}-1)^2$	0.765	0.379	2.107	0.000	18.775
absolute deviation of marginal q from one	$ \dot{q}-1 $	0.575	0.143	0.660	0.006	4.333
Panel C. Control variables						
absolute firm-specific fundamentals variation	$\ln(\sigma_{ROA, \varepsilon}^2)$	-5.888	-5.757	0.866	-9.058	-4.348
absolute systematic fundamentals variation	$\ln(\sigma_{ROA, m}^2)$	-5.943	-5.858	0.811	-8.817	-4.184
relative firm-specific fundamentals variation	${}_{ROA}\Psi$	0.055	0.115	0.550	-2.052	1.605
average q	\bar{q}	1.775	1.363	1.518	0.215	12.251
corporate diversification	$segs$	2.033	1.809	0.917	1.000	5.937
Herfindahl index	H	0.338	0.297	0.198	0.044	0.991
size	$\ln(K)$	9.010	9.090	1.681	4.267	13.811
liquidity	λ	0.274	0.236	0.231	-0.108	1.409
leverage	lev	0.297	0.262	0.189	0.004	1.208
advertising spending	adv	0.018	0.004	0.031	0.000	0.178
R&D spending	$r\&d$	0.030	0.011	0.045	0.000	0.237

Table III.a
**Simple Correlation Coefficients of Capital Budgeting Quality and Firm-specific
Stock Return Variation Variables with Each Other and with Control Variables**

This table reports correlation coefficients based on a 196 three-digit industries sample. Numbers in parentheses are probability levels at which the null hypothesis of zero correlation is rejected. Coefficients significant at 10 percent or better (based on 2-tail test) are in boldface. Refer to Table I for variable definitions. The return variation measures, σ_{ϵ}^2 , σ_m^2 , R^2 , $\ln(\sigma_{\epsilon}^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The quality of capital budgeting variables, $(\dot{q} - 1)^2$ and $|\dot{q} - 1|$, are constructed using 1993-to-1997 data for 196 three-digit industries spanned by 16,735 firm-year observations. The controls, \bar{q} , seg , H , $\ln(K)$, $\tilde{\lambda}$, lev , adv , and $r\&d$, are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The fundamentals variation controls, $\ln_{(ROA)}\sigma_{\epsilon}^2$, $\ln_{(ROA)}\sigma_m^2$, and $_{ROA}\Psi$, are constructed using 1983-to-1992 data for 196 three-digit industries spanned by 4,705 firms. To utilize as much information as possible to capture fundamental comovements, we include firms that might not last through out the period, but had at least six years of continuous data. Finance industries (SIC code 6000 - 6999) are omitted.

		\dot{q}	$(\dot{q}-1)^2$	$ \dot{q}-1 $	$\ln(\sigma_\varepsilon^2)$	Ψ
Panel A: Quality of capital budgeting variables						
marginal q	\dot{q}	-	-0.249 (0.00)	-0.131 (0.07)	-	-
absolute deviation of marginal q from 1	$ \dot{q}-1 $	-	0.915 (0.00)	-	-0.140 (0.05)	-0.113 (0.12)
Panel B: Firm-specific stock return variation						
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	0.040 (0.58)	-0.166 (0.02)	-	-	0.468 (0.00)
relative firm-specific stock return variation	Ψ	0.025 (0.72)	-0.129 (0.07)	-	-	-
Panel C: Control variables						
absolute systematic return variation	$\ln(\sigma_m^2)$	0.026 (0.71)	-0.091 (0.20)	-0.075 (0.30)	0.773 (0.00)	-0.199 (0.01)
absolute firm-specific ROA variation	$\ln(\sigma_{\varepsilon}^2)$	0.035 (0.62)	-0.059 (0.42)	-0.040 (0.58)	0.608 (0.00)	0.524 (0.00)
absolute systematic ROA variation	$\ln(\sigma_m^2)$	-0.045 (0.53)	-0.032 (0.65)	0.043 (0.55)	0.624 (0.00)	0.243 (0.00)
relative firm-specific ROA variation	Ψ	0.122 (0.09)	-0.044 (0.54)	-0.127 (0.08)	0.037 (0.61)	-0.028 (0.70)
average q	\bar{q}	0.018 (0.80)	-0.079 (0.27)	-0.054 (0.45)	0.308 (0.00)	0.083 (0.25)
corporate diversification	segs	-0.090 (0.21)	-0.078 (0.28)	-0.095 (0.18)	-0.163 (0.02)	0.060 (0.41)
Herfindahl index	H	-0.134 (0.06)	0.278 (0.00)	0.337 (0.00)	-0.043 (0.55)	0.034 (0.63)
industry size	$\ln(K)$	0.014 (0.85)	-0.282 (0.00)	-0.379 (0.00)	-0.187 (0.01)	-0.037 (0.61)
liquidity	$\tilde{\lambda}$	-0.077 (0.29)	0.041 (0.57)	0.075 (0.30)	0.172 (0.02)	-0.027 (0.71)
leverage	lev	0.048 (0.50)	-0.114 (0.11)	-0.068 (0.34)	0.133 (0.06)	0.083 (0.25)
advertising spending	adv	-0.082 (0.26)	0.022 (0.76)	-0.037 (0.61)	0.170 (0.02)	0.035 (0.63)
R&D spending	r&d	-0.044 (0.54)	-0.025 (0.73)	-0.018 (0.80)	0.012 (0.87)	-0.038 (0.59)

Table III.b
Simple Correlation Coefficients of Main Control Variables with Firm-specific Stock Return Variation Variables and with Each Other

This table reports correlation coefficients based on a 196 three-digit industries sample. Numbers in parentheses are probability levels at which the null hypothesis of zero correlation is rejected. Coefficients significant at 10 percent or better (based on 2-tail test) are in boldface. Refer to Table I for variable definitions. The sample is 196 three-digit industries for all variables. The return variation measures, σ_{ε}^2 , σ_m^2 , R^2 , $\ln(\sigma_{\varepsilon}^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1990-to-1992 data for a sample of 196 three-digit industries spanned by 4,029 firms. The controls, \bar{q} , segs, H, $\ln(K)$, λ , lev, adv, and r&d, are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The fundamentals variation controls, $\ln(\sigma_{\varepsilon}^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1983-to-1992 data for 196 three-digit industries spanned by 4,705 firms. To utilize as much information as possible to capture fundamental comovements, we include firms that might not last throughout the period, but had at least six years of continuous data. Finance industries (SIC code 6000 - 6999) are omitted.

$\ln(\sigma_{\varepsilon}^2)$	$\ln(\sigma_m^2)$	Ψ	\bar{q}	segs	H	$\ln(K)$	λ	lev	adv	r&d	r&d	R&D spending
0.524 (0.00)	0.518 (0.00)	0.061 (0.39)	0.282 (0.00)	-0.224 (0.00)	-0.073 (0.31)	-0.182 (0.01)	0.211 (0.00)	0.087 (0.22)	0.164 (0.02)	0.041 (0.57)	$\ln(\sigma_m^2)$	absolute systematic stock return variation
	0.787 (0.00)	0.415 (0.00)	0.338 (0.00)	-0.167 (0.02)	-0.073 (0.31)	-0.189 (0.01)	0.328 (0.00)	0.087 (0.22)	0.259 (0.00)	0.114 (0.11)	$\ln(\sigma_{\varepsilon}^2)$	absolute firm-specific fundamentals variation
		-0.236 (0.00)	0.362 (0.00)	-0.114 (0.11)	-0.019 (0.79)	-0.256 (0.00)	0.290 (0.00)	0.142 (0.05)	0.189 (0.01)	0.054 (0.45)	$\ln(\sigma_m^2)$	absolute systematic fundamentals variation
			-0.001 (0.99)	-0.094 (0.19)	-0.087 (0.22)	0.080 (0.26)	0.090 (0.21)	-0.072 (0.32)	0.129 (0.07)	0.100 (0.16)	Ψ	rel. firm-specific fundamentals variation
				-0.069 (0.34)	-0.109 (0.13)	-0.042 (0.56)	0.260 (0.00)	0.175 (0.01)	0.359 (0.00)	0.160 (0.02)	\bar{q}	average q
					0.233 (0.00)	0.244 (0.00)	-0.182 (0.01)	0.064 (0.37)	0.080 (0.26)	-0.112 (0.12)	segs	corporate diversification
						-0.293 (0.00)	-0.048 (0.50)	-0.024 (0.74)	-0.026 (0.72)	0.048 (0.51)	H	Herfindahl index
							-0.460 (0.00)	-0.052 (0.47)	0.217 (0.00)	-0.076 (0.29)	$\ln(K)$	size
								-0.141 (0.05)	0.109 (0.13)	0.305 (0.00)	λ	liquidity
									-0.176 (0.01)	-0.078 (0.28)	Lev	leverage
										0.022 (0.76)	Adv	advertising spending

Table IV

Ordinary Least Squares Regressions of Capital Budgeting Quality Variables (Measured as Deviation of Marginal q from One) on Firm-specific Stock Return Variation and Control Variables

This table reports Ordinary Least Squares regression estimation results. The dependent variables are capital budgeting quality measures $(\hat{q} - 1)^2$ (specifications 4.1-4.4) and $|\hat{q} - 1|$ (specifications 4.5-4.8). Regressions 4.1 and 4.5 include absolute firm-specific stock return variation, $\ln(\sigma_\varepsilon^2)$, absolute systematic stock return variation, $\ln(\sigma_m^2)$, absolute firm-specific fundamentals variation, $\ln(\sigma_{ROA}^2)$, and absolute systematic fundamentals variation, $\ln(\sigma_{ROA}^2)$, as independent variables. Regressions 4.2 and 4.6 also include corporate diversification (segs), Herfindahl index (H), size ($\ln(K)$), liquidity ($\tilde{\lambda}$), leverage (lev), advertising spending (adv), and R&D spending (r&d) as control variables. Regressions 4.3 and 4.7 also include average q (\bar{q}) as a control variable. Regressions 4.4 and 4.8 include relative firm-specific stock return variation, Ψ , relative firm-specific fundamentals variation, Ψ_{ROA} , average q (\bar{q}) corporate diversification (segs), Herfindahl index (H), size ($\ln(K)$), liquidity ($\tilde{\lambda}$), leverage (lev), advertising spending (adv), and R&D spending (r&d) as independent variables. All regressions also include one-digit SIC industry fixed effects (coefficients are not reported). Finance industries (SIC code 6000 - 6999) are omitted. Numbers in parentheses are probability levels, based on Newey-West (robust) standard errors, at which the null hypothesis of a zero coefficient can be rejected. Coefficients significant at 10 percent level, based on 2-tail tests, are in boldface. The return variation measures, σ_ε^2 , σ_m^2 , R^2 , $\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1990-to-1992 data for a sample of 196 three-digit industries spanned by 4,029 firms. The quality of capital budgeting variables, $(\hat{q} - 1)^2$ and $|\hat{q} - 1|$, are constructed using 1993-to-1997 data for 196 three-digit industries spanned by 16,735 firm-year observations. The controls, \bar{q} , seg, H, $\ln(K)$, $\tilde{\lambda}$, lev, adv, and r&d, are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The fundamentals variation controls, $\ln(\sigma_{ROA}^2)$, $\ln(\sigma_{ROA}^2)$, and Ψ_{ROA} , are constructed using 1983-to-1992 data for 196 three-digit industries spanned by 4,705 firms. To utilize as much information as possible to capture fundamental comovements, we include firms that might not last throughout the period, but had at least six years of continuous data. Refer to Table I for variable definitions.

	4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8
<i>dependent variable</i>	<i>squared deviation of marginal q from 1, $(\dot{q} - 1)^2$</i>				<i>absolute value of deviation of marginal q from 1, $\dot{q} - 1$</i>			
<i>absolute firm-specific stock return variation</i> $\ln(\sigma_\varepsilon^2)$	-0.701 (0.08)	-0.760 (0.04)	-0.730 (0.05)	-	-0.231 (0.06)	-0.245 (0.02)	-0.239 (0.03)	-
<i>absolute systematic stock return variation</i> $\ln(\sigma_m^2)$	0.310 (0.39)	0.306 (0.39)	0.295 (0.40)	-	0.083 (0.44)	0.080 (0.44)	0.077 (0.45)	-
<i>relative firm-specific stock return variation</i> Ψ	-	-	-	-0.531 (0.11)	-	-	-	-0.158 (0.09)
<i>absolute firm-specific fundamentals variation</i> $\ln(\sigma_{ROA}^2)$	0.001 (0.99)	0.073 (0.87)	0.070 (0.87)	-	-0.084 (0.51)	-0.059 (0.63)	-0.059 (0.62)	-
<i>absolute systematic fundamentals variation</i> $\ln(\sigma_m^2)$	0.212 (0.52)	0.087 (0.80)	0.140 (0.67)	-	0.198 (0.07)	0.145 (0.15)	0.156 (0.12)	-
<i>relative firm-specific fundamentals variation</i> $ROA \Psi$	-	-	-	-0.030 (0.94)	-	-	-	-0.105 (0.33)
<i>average q</i> \bar{q}	-	-	-0.193 (0.14)	-0.204 (0.13)	-	-	-0.041 (0.29)	-0.042 (0.27)
<i>corporate diversification</i> <i>segs</i>	-	-0.173 (0.21)	-0.169 (0.22)	-0.134 (0.29)	-	-0.076 (0.10)	-0.076 (0.10)	-0.065 (0.14)
<i>Herfindahl index</i> <i>H</i>	-	2.073 (0.03)	1.975 (0.03)	2.016 (0.02)	-	0.839 (0.01)	0.818 (0.00)	0.831 (0.00)
<i>size</i> $\ln(K)$	-	-0.381 (0.04)	-0.374 (0.04)	-0.361 (0.05)	-	-0.131 (0.00)	-0.129 (0.00)	-0.125 (0.01)
<i>liquidity</i> $\hat{\lambda}$	-	-0.859 (0.24)	-0.599 (0.37)	-0.472 (0.45)	-	-0.175 (0.45)	-0.120 (0.58)	-0.061 (0.77)
<i>leverage</i> <i>lev</i>	-	-1.306 (0.02)	-1.026 (0.07)	-1.120 (0.05)	-	-0.319 (0.12)	-0.260 (0.21)	-0.285 (0.17)
<i>advertising spending</i> <i>adv</i>	-	9.115 (0.26)	13.516 (0.18)	12.612 (0.20)	-	1.751 (0.42)	2.676 (0.33)	2.400 (0.37)
<i>R&D spending</i> <i>R&d</i>	-	-1.916 (0.43)	-0.916 (0.73)	-0.840 (0.75)	-	-0.574 (0.46)	-0.364 (0.67)	-0.338 (0.69)
<i>F-statistics</i>	3.54 (0.00)	1.87 (0.02)	1.83 (0.02)	1.91 (0.02)	8.57 (0.00)	3.35 (0.00)	3.22 (0.00)	3.21 (0.00)
<i>Regression R²</i>	0.124	0.278	0.288	0.277	0.121	0.326	0.330	0.314

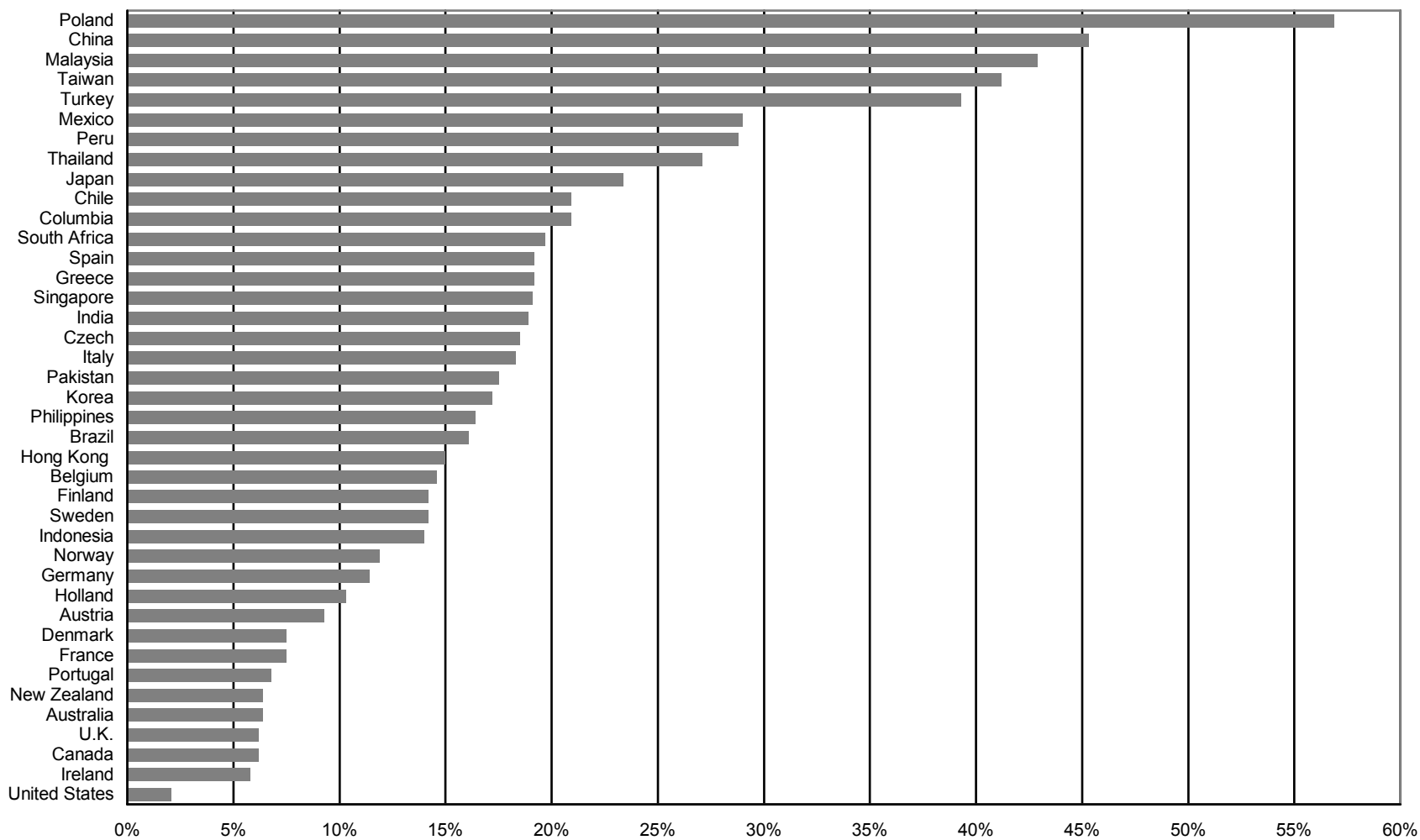
Table V

Non-Linear Least Squares Regressions of the Capital Budgeting Quality Measures (Measured as Deviation from Threshold Value) on Firm-specific Stock Return Variation and Control Variables

This table reports Non-Linear Least Squares regression estimation results. The dependent variables are capital budgeting quality measures $(\dot{q} - h)^2$ (specifications 5.1 - 5.4) and $|\dot{q} - h|$ (specifications 5.5 - 5.8) where the threshold level h is estimated endogenously. Regressions 5.1 and 5.5 include absolute firm-specific stock return variation, $\ln(\sigma_\varepsilon^2)$, absolute systematic stock return variation, $\ln(\sigma_m^2)$, absolute firm-specific fundamentals variation, $\ln({}_{ROA}\sigma_\varepsilon^2)$, and absolute systematic fundamentals variation, $\ln({}_{ROA}\sigma_m^2)$, as independent variables. Regressions 5.2 and 5.6 also include corporate diversification (segs), Herfindahl index (H), size ($\ln(K)$), liquidity (λ), leverage (lev), advertising spending (adv), and R&D spending (r&d) as control variables. Regressions 5.3 and 5.7 also include average q (\bar{q}) as a control variable. Regressions 5.4 and 5.8 include relative firm-specific stock return variation, Ψ , relative firm-specific fundamentals variation, ${}_{ROA}\Psi$, average q , corporate diversification (segs), Herfindahl index (H), size ($\ln(K)$), liquidity (λ), leverage (lev), advertising spending (adv), and R&D spending (r&d) as independent variables. All regressions also include one-digit SIC industry fixed effects (coefficients are not reported). The sample is 196 three-digit industries. Finance industries (SIC code 6000 - 6999) are omitted. Numbers in parentheses are probability levels at which the null hypothesis of zero coefficient can be rejected. Coefficients significant at 10 percent level (based on 2-tail test) are in boldface. For each specification, Wald test statistics of the hypothesis that the threshold level h is equal to one is reported. The return variation measures, σ_ε^2 , σ_m^2 , R^2 , $\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, and Ψ , are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The quality of capital budgeting variables, $(\dot{q} - 1)^2$ and $|\dot{q} - 1|$, are constructed using 1993-to-1997 data for 196 three-digit industries spanned by 16,735 firm-year observations. The controls, \bar{q} , seg, H, $\ln(K)$, λ , lev, adv, and r&d, are constructed using 1990-to-1992 data for 196 three-digit industries spanned by 4,029 firms. The fundamentals variation controls, $\ln({}_{ROA}\sigma_\varepsilon^2)$, $\ln({}_{ROA}\sigma_m^2)$, and ${}_{ROA}\Psi$, are constructed using 1983-to-1992 data for 196 three-digit industries spanned by 4,705 firms. To utilize as much information as possible to capture fundamental comovements, we include firms that might not last through out the period, but had at least six years of continuous data. Refer to Table I for variable definitions.

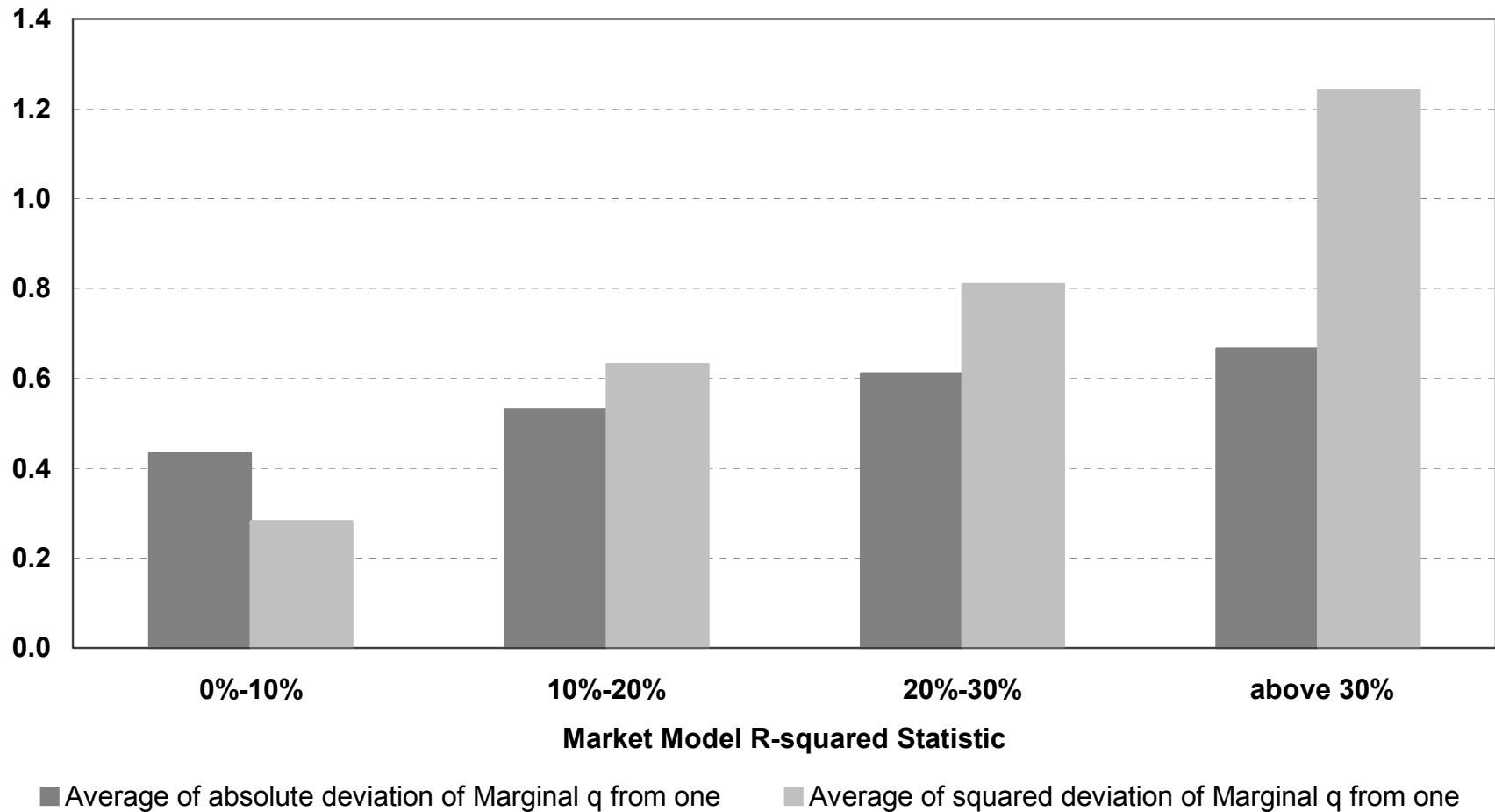
	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
<i>dependent variable</i>	<i>squared deviation of marginal q from an endogenously estimated threshold value h, $(\hat{q} - h)^2$</i>				<i>absolute value of deviation of marginal q from an endogenously estimated threshold value h, $\hat{q} - h$</i>			
<i>threshold value of marginal q</i> h	0.755 (0.00)	0.773 (0.00)	0.780 (0.00)	0.777 (0.00)	0.715 (0.00)	0.820 (0.00)	0.868 (0.00)	0.908 (0.00)
<i>F-statistics of Wald test to reject h equal to 1</i>	8.15 (0.00)	7.93 (0.01)	7.42 (0.01)	7.60 (0.01)	11.37 (0.00)	5.03 (0.03)	2.83 (0.09)	1.35 (0.25)
<i>absolute firm-specific stock return variation</i> $\ln(\sigma_\varepsilon^2)$	-0.655 (0.04)	-0.717 (0.02)	-0.692 (0.02)		-0.754 (0.00)	-0.575 (0.00)	-0.538 (0.00)	
<i>absolute systematic stock return variation</i> $\ln(\sigma_m^2)$	0.302 (0.35)	0.282 (0.36)	0.273 (0.37)		0.693 (0.00)	0.085 (0.59)	0.085 (0.61)	
<i>relative firm-specific stock return variation</i> Ψ				-0.507 (0.05)				-0.410 (0.01)
<i>absolute firm-specific fundamentals variation</i> $\ln(\text{ROA}\sigma_\varepsilon^2)$	0.079 (0.78)	0.146 (0.60)	0.141 (0.61)		0.803 (0.00)	0.280 (0.03)	0.485 (0.00)	
<i>absolute systematic fundamentals variation</i> $\ln(\text{ROA}\sigma_m^2)$	0.105 (0.73)	-0.009 (0.97)	0.041 (0.89)		-0.740 (0.00)	-0.108 (0.47)	-0.275 (0.06)	
<i>relative firm-specific fundamentals variation</i> $\text{ROA}\Psi$				0.054 (0.83)				0.311 (0.01)
<i>average q</i> \bar{q}			-0.170 (0.18)	-0.182 (0.14)			-0.245 (0.00)	-0.259 (0.00)
<i>corporate diversification</i> <i>segs</i>		-0.204 (0.23)	-0.200 (0.24)	-0.164 (0.32)		-0.178 (0.06)	-0.122 (0.19)	-0.129 (0.20)
<i>Herfindahl index</i> H		1.813 (0.03)	1.735 (0.03)	1.773 (0.03)		1.041 (0.00)	0.771 (0.04)	1.023 (0.01)
<i>size</i> $\ln(K)$		-0.396 (0.00)	-0.389 (0.00)	-0.375 (0.00)		-0.315 (0.00)	-0.303 (0.00)	-0.274 (0.00)
<i>liquidity</i> $\hat{\lambda}$		-0.962 (0.22)	-0.730 (0.36)	-0.624 (0.43)		-1.452 (0.00)	-0.910 (0.03)	-0.444 (0.28)
<i>leverage</i> <i>lev</i>		-1.235 (0.12)	-0.990 (0.22)	-1.092 (0.17)		-0.778 (0.08)	-0.866 (0.04)	-0.959 (0.02)
<i>advertising spending</i> <i>adv</i>		8.606 (0.11)	12.494 (0.04)	11.548 (0.06)		11.027 (0.00)	14.524 (0.00)	12.331 (0.00)
<i>R&D spending</i> <i>r&d</i>		-2.257 (0.49)	-1.366 (0.68)	-1.297 (0.70)		-2.391 (0.24)	-1.745 (0.37)	-0.501 (0.82)
<i>F-statistics</i>	7.24 (0.00)	7.37 (0.00)	7.14 (0.00)	7.73 (0.00)	19.28 (0.00)	19.59 (0.00)	20.3 (0.00)	20.45 (0.00)
<i>Regression R²</i>	0.341	0.457	0.463	0.455	0.597	0.702	0.720	0.699

Figure 1
Stock Return Synchronicity in Various Countries as Measured by the Average R^2 of Regressions of Firm Returns on Domestic and US Market Returns



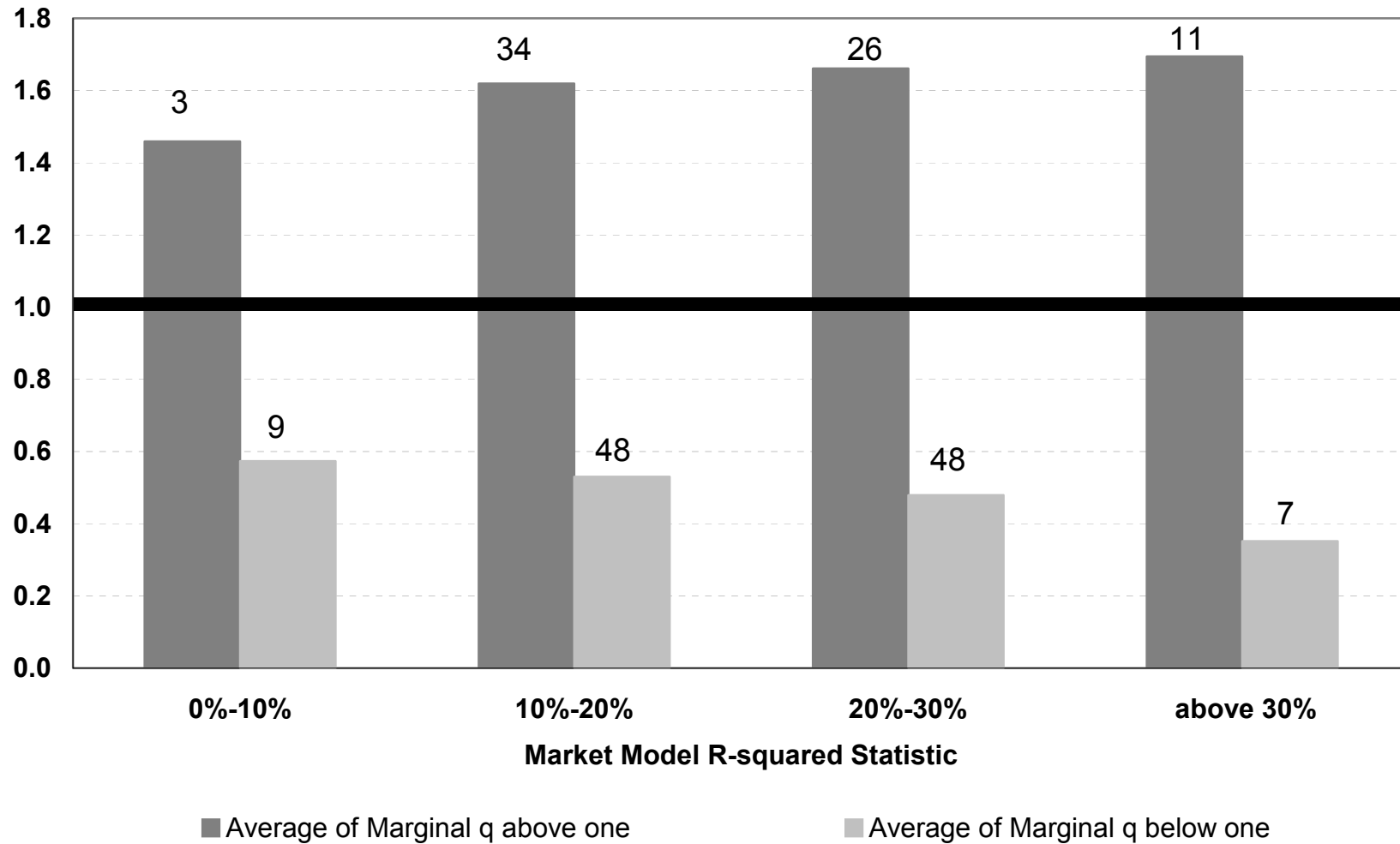
Source: Morck, Yeung, and Yu (2000).

Figure 2
The Deviation of Marginal Tobin's q from One with Industries Grouped by Industry-Average Firm-Level Market Model R^2 .



A low R^2 indicates high firm-specific return variation relative to market and industry-related variation. The height of each bar is the group average deviation of marginal q below and above one.

Figure 3
Mean Marginal q for Industries Subsamples with Marginal q Above One and Below One, Grouped by Industry-Average Firm-Level Market Model R^2 .



A low R^2 indicates high firm-specific return variation relative to market and industry-related variation. The height of each bar is the group mean marginal q . The number of observations in each group is listed at the top of each bar. The sample sizes for 0% to 10%, 10% to 20%, 20% to 30% and 30% to 40% are 3, 34, 26, and 11 industries with marginal q above one and 9, 48, 48, and 7 industries with marginal q below one.