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Value Enhancing Capital Budgeting and Firm-Specific Stock Returns Variation

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Abstract

A major issue in corporate finance is the extent to which managers' decisions enhance firm value. We show that capital budgeting decisions are more consistent with value maximization in industries whose stocks exhibit greater firm-specific return variation. This finding argues against the view that firm-specific return variation is noise, and supports Roll's (1988) view that firm-specific return variation indicates activity by risk arbitrageurs. Given this, we argue that corporate investment decisions tend to be more firm value enhancing where firm-specific risk arbitrage activity is greater.

1. Introduction

It is plausible that the extent to which stock prices approximate fundamental (full information) values is related to the extent to which corporate capital budgeting decisions enhance firm market value. First, stock prices play critical signaling and incentive alignment roles in many corporate governance mechanisms that can curb the sorts of self-serving or inept managerial behavior that lead to non-value-maximizing capital budgeting decisions.[1] For example, shareholder derivative lawsuits, executive stock options, and the market for corporate control all depend upon the efficiency of the stock market as an information processor. Second, stock prices convey information about investors' perceptions to managers. Stock price reactions to managers' decisions can provide useful feedback that improves corporate governance (and so

[1] See e.g. Amihud and Lev (1981), Shleifer and Vishny (1989), Jensen (1986). See Stein (2001) for a survey.

capital budgeting) if shareholders are well informed. Third, the more informed investors are, the easier it is for managers to raise external financing to fund value-enhancing projects.

Thus, a higher incidence of value enhancing corporate capital budgeting decisions should be evident where stock prices are better informed, by which we mean that a greater fraction of public and private information is capitalized into the stock price. To empirically examine this proposition requires two steps:

First, we need a measure of how informed stock prices are. To do this, we follow Roll (1988) and distinguish firm-specific returns variation from market-related and industry-related returns variation. Roll shows that common asset pricing models have low R^2 statistics because of high firms-specific return variation *not associated with public information*. He argues that "the financial press misses a great deal of relevant information generated privately" (p. 564), and concludes that this firm-specific returns variation reflects the capitalization of private information into share prices as a result of informed trading by risk arbitrageurs. However, he concedes (p. 56) that firm-specific returns variation might reflect "either private information or else occasional frenzy unrelated to concrete information."

If firm-specific returns variation reflects investor frenzy, it is larger when prices are less informed. If firm-specific returns variation reflects the capitalization of private firm-specific information, several possibilities arise. First, greater firm-specific variation might again reflect less informed pricing because mispricing must exist to attract arbitrageurs. Second, greater firm-specific variation might be unrelated to how informed stock prices are because arbitrageur activity keeps all stock prices roughly equally informed. Third, greater firm-specific variation might reflect more informed pricing, perhaps because the presence of informed arbitrageurs reduces the influence of noise traders, as in De Long *et al.* (1986).

Second, we require a measure of the extent to which corporate capital budgeting decisions enhance firm market value. To achieve that, we directly estimate Tobin's marginal q ratios, one plus the net present value (NPV) of the firm's marginal capital budgeting project over its set-up cost, all as perceived by investors. The deviation of Tobin's marginal q, based on firm market value, from its optimal level (which is one when tax factors are ignored) measures the extent to which firms' capital budgeting decisions enhance firm market value.

We find highly significant and robust empirical evidence that greater firm-specific stock return variation is associated with marginal q ratios closer to its optimal level. This finding is consistent with the joint hypothesis that more informed stock prices are associated with capital budgeting more aligned to market value maximization and that greater firm-specific stock returns variation is indicative of more informed stock prices. That is, high firm-specific returns variation, far from reflecting investor frenzy, signifies the capitalization of private information into stock prices through risk arbitrage trading, which leads to more informed, rather than less informed, stock prices.

Section 2 explains our firm specific stock return variation variables, while section 3 explains our measure of the quality of corporate capital budgeting decisions. Section 4 describes our empirical estimation techniques and our main control variables. Section 5 presents our empirical results, and section 6 reports robustness checks. Section 7 discusses our results and section 8 concludes. The appendix contains details about the construction of our data and a complete description of our marginal q estimation technique.

2. Firm-Specific Returns Variation

2.1 Motivation

Information about fundamentals is capitalized into stock prices *via* two channels: a general revaluation of stock values following the release of public information (such as Fed interest rate announcements or SEC filings), and the trading activity of risk arbitrageurs who gather and possess private information. Shleifer and Vishny (1997a) argue that risk arbitrage is limited, and may be more limited in some circumstances than others.

Roll (1988) concludes that firm-specific return variation could reflect either the capitalization of private information into stock prices by informed risk arbitrageurs or investor frenzy. Current evidence suggests that Roll's former interpretation is more plausible.

First, Figure 1 shows the average R^2 statistics of regressions of firm-level stock returns on local and US market returns using 1995 data for a range of countries, as reported by Morck et al. (2000). These R^2s 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 et al. (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 propose that low average market model R^2s reflect greater activity by the risk arbitrageurs Roll (1988) posits as responsible for firm-specific price movements, and conjecture that a low market model R^2 may actually mark a more efficient stock market.

Second, Durnev et al. (2001) show that stock returns more accurately predict future earnings changes in industries where returns are less synchronous, as measured by a market model R^2 statistic. Collins et al. (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 a higher information content when firm-specific variation is a larger fraction of total variation.

Finally, Wurgler (2000) shows that capital flows are more responsive to changes in value-added in countries exhibiting less synchronous stock returns. This suggests that capital moves more quickly to its highest value uses in countries whose stocks move 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).

We nonetheless retain an ecumenical attitude, and allow the data to suggest the best interpretation of firm-specific returns variation.

2.2 Measuring Firm-Specific Returns Variation

This section describes the estimation of our firm-specific return variation measures. Its contents are summarized in Table 1. The data used in this estimation procedure are daily total returns for 1990 through 1992 for the 6,021 firms for which both CRSP and Compustat data exist. These firms span 214 three-digit SIC industries. The construction of the dataset is described in detail in the appendix.

We gauge firm-specific return variation by regressing the return of the stock of firm *j* in industry *i*, $r_{i,j,t}$, on market and industry returns, $r_{m,t}$ and $r_{i,t}$.

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

for each firm *j* in industry *i*, where *t* is a daily time index over the period from 1990 through 1992, $r_{i,j,t}$ is firm *j*'s stock return, $r_{m,t}$ is a market return, and $r_{i,t}$ an industry return for industry *i* (which contains firm *j*). The market index and industry indices in [1] are value-weighted averages excluding the firm in question. This exclusion prevents spurious correlations between firm returns and industry returns in industries that contain few firms. One minus the average R^2 of regression [1] for all firms in an industry is a measure of the importance of firm-specific return variation in that industry, and we interpret this as gauging the activity of risk arbitrageurs capitalizing private information.

Although regression [1] resembles standard asset pricing equations, we do not emphasize this. Our purpose is not to explain a relationship between returns and systematic risk, but to understand the economic importance of firm-specific stock price variation. Stock price variation associated with macroeconomic or industry information is of interest to us primarily as a control variable. Note also that we depart from the standard terminology of asset pricing and 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, though this is not strictly correct. We decompose return variation in this way because Roll (1988) specifically links arbitrage that capitalizes private information to firm-specific variation.

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

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

where

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

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

Since $\sigma^2_{\varepsilon,i}$ and $\sigma^2_{m,i}$ have skewness coefficients of 5.31 and 5.30 respectively and kurtoses of 40.7 and 36.7 respectively, we apply a logarithmic transformation. The distributions of $\ln(\sigma^2_{\varepsilon,i})$ and $\ln(\sigma^2_{m,i})$ are both more symmetric (skewness coefficients of 0.16 and 0.52 respectively) and less leptokurtic (kurtoses of 4.11 and 4.59 respectively).

The distribution of $1-R_i^2$ is also negatively skewed (*skewness* = -0.91) and mildly leptokurtic (*kurtosis* = 4.64). 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 by applying a logistic transformation

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

taking $1\text{-}R_i^2 \in [0,1]$ to $\Psi_i \in \Re$. We thus use the Greek letter *psi* to denote firm-specific stock return variation measured relative to variations due to industry- and market-wide factors. The transformed variable is again less skewed (*skewness* = 0.24) and less leptokurtic (*kurtosis* = 3.87). The hypothesis that Ψ_i is normally distributed cannot be rejected in a standard W-test (*p-value* = 0.14).

The transformed variable Ψ_i also possesses the useful trait that

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

Intuitively, the higher the value of Ψ_i, the more important is firm-specific variation, $\sigma^2_{\varepsilon,i}$, *relative to* market and industry-wide variation, $\sigma^2_{m,i}$, in explaining the stock price movements of firms in industry *i*.

In the following, we refer to $\ln(\sigma^2_{\varepsilon,i})$ as *absolute firm-specific stock return variation*, $\ln(\sigma^2_{m,i})$ as *absolute systematic stock return variation*, and Ψ_i as *relative firm-specific stock return variation*.

Table 1 contains brief descriptions of these variables, and of all other variables used in this study. Panel A of Table 2 shows the mean, standard deviation, minimum and maximum of each measure of stock return variations: $\ln(\sigma^2_{\varepsilon,i})$, $\ln(\sigma^2_{m,i})$ and Ψ_i. The substantial standard deviations of all three measures and the substantial difference between their minimum and maximum values attest to their variation across industries. Higher firm-specific and systematic stock return variations tend to occur together ($\rho = 0.761$, $p\text{-}val = 0.00$).[2]

3. Tobin's Marginal *q* Ratio

3.1 Motivation

Optimal capital budgeting consists of undertaking all available projects with positive expected net present value (NPV) and avoiding all those projects with negative expected NPV. The NPV of a project is the present value of the net cash flows, cf_t, it 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

[2] In our sample, examples of high firm-specific stock return variation industries include: commercial sports, knitting mills, crude petroleum & natural gas, periodical publications, and tobacco. Examples of low firm-specific stock

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

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 make the NPV of corporate capital expenditure comparable across firms, we scale by set up costs to obtain a profitability index (PI). Optimal capital budgeting entails undertaking a project if and only if its expected profitability index surpasses one.

$$\mathrm{E}_{mgt}[PI] = \frac{1}{C_0}\mathrm{E}_{mgt}\left[\sum_{t=1}^{\infty} \frac{cf_t}{(1+r)^t}\right] = 1 + \frac{\mathrm{E}_{mgt}[NPV]}{C_0} > 1 \qquad [7]$$

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

The change in firm market value due to its (unexpected) capital expenditure equals investors' estimate of the NPV of the projects undertaken. The change in the value of a firm associated with a unit increase in its stock of capital goods (replacement cost) is the firm's marginal Tobin's *q* ratio, denoted

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

where we redefine C_0 to be the total setup cost of all projects undertaken this period, cf_t to be the total cash flows those projects generate in future periods *t*, and E_s to investors' expectations.

In summary, market value maximizing corporate investment requires that managers undertake all projects to which investors assign positive NPVs and no projects to which investors assign negative NPVs. A firm that follows this strategy should have a Tobin's marginal q ratio approximately equal to one. Tax factors, discussed in more detail below, can cause value

return variation industries include engines and turbines, general building constructors, department stores, drug and proprietary stores, electric, gas and other services (regulated industries), and operative builders.

maximization to push marginal q's towards a threshold value slightly different from one. We account for tax factors in our empirical tests.

We wish to see in which industries marginal q, as depicted in [8], is close to its optimal value. Where marginal q exceeds its optimal value, we may infer underinvestment. Likewise, where marginal q is below its optimal value, we may infer overinvestment. We discuss reasons why marginal q might differ from its value maximizing level in the next section. We now explain our procedure for estimating marginal q.

3.2 Measuring Tobin's Marginal *q* Ratio

To obtain reliable estimates of the impact of investment on firm market value, we must use annual data. (Quarterly financial data are unaudited). If we used a long time window to estimate our variables, it is likely that shifting technological constraints, market conditions, and governance changes would make our estimates unreliable. Also, relying only on firms with data available for many years creates a survival bias and makes our estimates unrepresentative of all firms. We therefore pool cross-section and time-series data over the relatively short window from 1993 to 1997 to construct more reliable industry-level marginal Tobin's q ratio estimates. To match this, our firm-specific stock return variation and control variables are also industry average measures.

The estimation procedure we use to estimate marginal q ratios, as defined in [8], is complicated, and a full description is provided in the appendix. The following is a brief overview.

Our basic approach is to write the marginal q of firm j as the ratio

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

where $V_{j,t}$ and $A_{j,t}$ are the market value (equity value plus debt value) 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.[3] The expected market value of the firm in period t is its market value in period t-1 augmented by the expected return from owning the firm, $\hat{r}_{j,t}$, and its disbursements to investors, which includes cash dividends, share repurchases, and interest expenses, $\hat{d}_{j,t}$.[4] 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 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

$$\frac{V_{j,t} - V_{j,t-1}}{A_{j,t-1}} = -\dot{q}_j(g_j - \delta_j) + \dot{q}_j \frac{A_{j,t} - A_{j,t-1}}{A_{j,t-1}} + r_j \frac{V_{j,t-1}}{A_{j,t-1}} - \xi_j \frac{div_{j,t-1}}{A_{j,t-1}} \qquad [10]$$

where ξ_j is a tax wedge measure.[5]

We can estimate [10] as a regression

$$\frac{\Delta V^i_{j,t}}{A^i_{j,t-1}} = \alpha^i + \beta^i_0 \frac{\Delta A^i_{j,t}}{A^i_{j,t-1}} + \beta^i_1 \frac{V^i_{j,t-1}}{A^i_{j,t-1}} + \beta^i_2 \frac{div^i_{j,t-1}}{A^i_{j,t-1}} + u^i_{j,t} \qquad [11]$$

[3] 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.

[4] 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.

[5] This relationship can also be derived as an Euler equation resulting from the firm's intertemporal value maximization problem.

across all firms j in industry i at time t. We pool firm observations to estimate an industry average marginal q ratio $\dot{q}_i \cong \beta_0^i$ for each of 214 three-digit nonfinancial industries i using 1993 to 1997 annual data. Details about the construction of this dataset and the precise econometric specification of the regressions are presented in the appendix.

Summary statistics of our marginal Tobin's q ratio estimates are presented in panel B of Table 2. The average marginal q across our sample of industries is 0.69, with a standard deviation of 0.64, a minimum value of -2.45 and a maximum value of 2.68. These estimates are consistent with a prevalence of overinvestment in the US nonfinancial corporate sector in the mid 1990s.

The average estimated values of β_1^i and β_2^i are broadly consistent with their interpretations in [10]. The average estimated coefficient β_1^i (the coefficient of lagged average q) is 0.104, implying an average cost of capital of 10.4%. The average estimated value of β_2^i on the disbursement rate is -0.799, and is insignificantly different from negative one at 10% level in 63 out of 214 industries. The average intercept, $\alpha^i = -\dot{q}_j(g_{j,t} - \delta_{j,t})$, is -0.048, and is insignificantly different from zero at 10% level in 110 out of 214 industries.

Additional collaborative evidence adds credence to our marginal q estimates. The regression coefficient $\alpha^i = -\dot{q}_j(g_{j,t} - \delta_{j,t})$ is indeed negative and significantly correlated with growth in physical capital. Also, β_1^i is indeed highly significantly positively correlated with estimated weighted average costs of capital.

We are interested in whether firm-specific stock return variation is associated with the distance of marginal q's from its optimal value, which we temporarily assume to be one. We measure the distance between $\dot{q}$ and one as either $(\dot{q}-1)^2$, the square of marginal q minus one, or as $|\dot{q}-1|$, the absolute value of marginal q minus one. The former metric places a heavier weighting of extreme values of marginal q.

Summary statistics of $\dot{q}$, $(\dot{q}-1)^2$ and $|\dot{q}-1|$ are therefore presented together in panel B of Table 2. For ease of exposition, we shall refer to $(\dot{q}-1)^2$ and $|\dot{q}-1|$ as measures of the *quality of capital budgeting* decisions, though they are more properly regarded as measures of investors' aggregated opinions about the quality of capital budgeting decisions.

4. Empirical Framework

4.1 Motivation

We wish to understand under what circumstances marginal q deviates from its market value maximizing level. Three possibly overlapping cases are worthy of note.

4.1.1 **Corporate Governance Problems**

Marginal q can deviate from its value maximizing level because of agency problems. Managers may distort capital budgeting policies in ways that advance their individual self-interest, as modeled by Jensen and Meckling (1976), Shleifer and Vishny (1989), and others. Managers might overinvest because of free cash flow problems, empire building, etc.; or they might underinvest because they are exposed to firm-specific risk that diversified investors ignore. Alternatively, managers may be ill informed or simply incompetent, and hence unable to identify their firm's optimal capital budgeting policy. Roll's (1986) hypothesis, that hubris can induce managers to overestimate their ability to generate positive NPVs, is an example of the latter sort of agency problem.

A range of corporate governance mechanisms, surveyed by Shleifer and Vishny (1997b), limits such agency problems. These include shareholder derivative lawsuits, executive stock options, board oversight, hostile takeovers, institutional investors, and various other mechanisms that align top managers' incentives to value maximization. For example, shareholder derivative lawsuits can be launched by any shareholder against managers whose decisions caused the value of the firm to fall precipitously. Performance based compensations reward CEOs when their stock price rises, boards sack CEOs when their firms' stock underperforms the stocks of industry peers, raiders launch takeovers of firms with sagging stock prices, and institutional investor activism is often triggered by lagging share prices. Finally, feedback from the trades of informed investors can cause ill-informed CEOs to learn.

These corporate governance mechanisms are most likely to function properly when share prices are good estimates of fundamental values. Shareholder derivative lawsuits, proxy fights, and hostile takeovers are all mechanisms that remove managers when the share price falls unacceptably, so as to replace them with new managers who will better maximize the market value of the firm. Performance based compensations reward managers when share prices rise, so as to retain a value maximizing management team. Most obviously, share prices make the most sense as a feedback mechanism when they include as much information as possible.

Where boards, raiders, and shareholders themselves regard the share price as an accurate estimate of fundamental value, these mechanisms drive marginal q ratios to their optimal levels. Where the share price is widely believed to be a poor indicator of fundamental value, these mechanisms work poorly, and may be deliberately disabled by managers.

Or, if not disabled, these corporate governance mechanisms may misfire in response to false stock price signals, rewarding poor managers and punishing good managers inappropriately. This dearth of informed oversight leaves greater scope for managerial discretion in capital budgeting, and consequently permits managerial self-interest, error, and incompetence.

For all of these corporate governance considerations, it is plausible that capital budgeting should more closely approximate market value maximization where share prices are better informed.

4.1.2 Investors with Imperfect Information

We treated the case of managers being less informed than investors as a corporate governance problem. We now turn to the case of managers being better informed than investors, as when managers possess inside information.

The deviation of marginal q in [8] from its optimal value is the shareholders' estimate of the market value added by a marginal unit of capital investment. If managers have information shareholders do not have, they may seek to disable market value-based corporate governance mechanisms so as to maximize fundamental, rather than market value, for example, as in Stein (1996). Observed marginal q would then deviate from its theoretical optimum.

If managers have better information than shareholders, Myers and Majluf (1984) argue that shareholders rationally expect managers to issue more securities when outstanding securities are overvalued in the market. Consequently, investors bid down any security's price on news that more of it will be issued, raising firms' costs of external capital. This "lemons problem" creates a discontinuity in the cost of capital when firms exhaust their internal funds and must seek outside financing. This discontinuity can induce firms to cease investing when its internal funds are exhausted, even though its last inframarginal project's NPV is well above zero. This is because the NPV of its next project, evaluated at the higher cost of capital associated with external funds, is well below zero. This would lead us to observe q ratios above the theoretical optimum.

In a similar vein, Hubbard (1998) argues that liquidity constraints are commonplace in the economy, and that these lead to pervasive underinvestment, and consequently to observed marginal qs above the theoretical optimum. These liquidity constraints often arise from banks or investors fears that insiders possess confidential information, or that insiders may misuse the funds advanced.

These information asymmetry problems are mitigated when shareholders are more nearly as informed as managers. If investors have more nearly as much information as managers, shareholder value maximization better approximates fundamental value maximization, the “lemons problem” of Myers and Majluf (1984) is reduced, and managers can more easily demonstrate their competence and ethics to overcome liquidity constraints. Better functioning corporate governance mechanisms, which we tied above to better-informed stock prices, also relax liquidity constraints by reassuring investors about the quality of management. However, if share prices are poorly informed, information asymmetry problems (like corporate governance problems) become more acute.

4.1.3 “Lumpy” Investment

Capital budgeting projects are often large discrete decisions, rather than a continuum of small decisions. Finance theory posits that firms rank their projects from highest to lowest profitability index along a marginal investment opportunity schedule, and undertake all those with profitability indexes above one. Lumpiness (discontinuity) in a firm’s investment opportunity schedule can cause a firm to stop investing even though its most recent inframarginal projects has an NPV substantially above zero. This is because the next project has a substantially negative NPV. If such lumpiness is commonplace, our marginal q ratio estimates should tend to exceed their theoretical optima.

4.1.4 Summary

Our objective is to examine the relationship between firm-specific stock return variation and the alignment of capital budgeting to market value maximization.

If firm-specific return variation reflects investor frenzy, greater firm-specific return variation should *ceteris paribus* be associated with capital budgeting that is less aligned to market value maximization. That is, the estimated marginal q, β_0^i in [11], should be farther from its theoretical optimum.

If higher firm-specific return variation reflects activity by informed risk arbitrageurs, we must consider three cases. If this arbitrage is financially possible because share prices are far from fundamentals and incomplete arbitrage drives them only partially back to fundamentals, capital budgeting might again be less aligned to market value maximization. If risk arbitrage roughly equates the distance between stock prices and fundamental values across the economy, we should expect no relationship between firm-specific returns variation and the alignment of capital budgeting to market value maximization. Finally, if informed arbitrage pushes stocks close to fundamentals, or reduces systematic variation created by noise trading as suggested by De Long *et al.* (1986), then greater firm-specific return variation might *ceteris paribus* be associated with more firm market value enhancing capital budgeting. That is, the estimated marginal q, β_0^i in [11], might be closer to its optimal value.

In each of these cases, we are interested in the association, all else equal, between firm-specific stock return variation and the quality of capital budgeting, as measured by the proximity of marginal q to its theoretical optimum. Firm specific stock return variation is intrinsically linked to firm-specific fundamental value variation. Therefore, we must try to control for firm specific fundamentals' variation as thoroughly as possible.

4.2 Simple Correlation Coefficients

Before discussing our multivariate regressions with control variables, it is interesting to examine the simple correlation coefficients between our capital budgeting quality measures, $(\dot{q}-1)^2$ and $|\dot{q}-1|$, and our firm-specific stock return variation variables, presented in Table 3a. For the moment, without considering tax factors, we interpret $(\dot{q}-1)^2$ and $|\dot{q}-1|$ as indicators of the deviation of capital budgeting decisions from their optimal. Marginal q tends to be closer to one in industries where stock returns exhibit greater firm-specific variation as measured by both absolute firm-specific return variation, $\ln(\sigma^2_{\varepsilon,i})$, and relative firm-specific stock return variation Ψ_i.

Note also that deviation of marginal q from 1 is insignificantly related to systematic variation $\ln(\sigma^2_{m,i})$ and that $\dot{q}$ itself is uncorrelated with all three stock return variation measures - $\ln(\sigma^2_{\varepsilon,i})$, $\ln(\sigma^2_{m,i})$, and Ψ_i.

Figures 2 and 3 illustrate these patterns. These figures group industries by the average R^2 of regression [1]. This is done for ease of interpretation, and is equivalent to grouping industries by $\Psi_i = \ln\left(\frac{1-R_i^2}{R_i^2}\right) = \ln\left(\frac{\sigma^2_{\varepsilon,i}}{\sigma^2_{m,i}}\right) = \ln(\sigma^2_{\varepsilon,i}) - \ln(\sigma^2_{m,i})$. A high R^2 corresponds to a low level of firm-specific return variation relative to systematic (market and industry-related) variation. Figure 2 shows that a low R^2, indicating a high level of firm-specific variation relative to systematic variation, is associated with marginal q ratios clustering more closely around one. Figure 3 shows that higher R^2 is associated with higher incidences of marginal qs both significantly below one and significantly above one.

These simple correlations and graphical representations of our data suggest that greater firm specific stock return variation is associated with higher standards of capital budgeting decisions. However, simple correlation coefficients of firm-specific return variation with capital budgeting quality are inadequate for our purposes. This is because some firms might have more firm-specific variation in their fundamental values than other firms. To some extent, we are controlling for this in Ψ_i by scaling firm-specific variation relative to market and industry-related variation; however, it is desirable to deal with this issue more directly.

4.3 Multivariate Regression Specification

We wish to determine whether, *all else equal*, greater firm-specific stock return variation is associated with more or less (or no relationship) firm value enhancement in corporate capital budgeting decision. This requires controlling for other factors that affect the quality of capital budgeting, and for latent common factors related to both capital budgeting quality and firm-specific returns variation.

Our regressions are thus of the form

$$
\begin{aligned}
|\dot{q}_i - 1| &= b_\Psi \Psi + \mathbf{c}' \cdot \mathbf{Z_i} + u_i \\
|\dot{q}_i - 1| &= b_\varepsilon \ln(\sigma^2_{\varepsilon,i}) + b_m \ln(\sigma^2_{m,i}) + \mathbf{c}' \cdot \mathbf{Z_i} + u_i
\end{aligned}
\qquad [12]
$$

where $\mathbf{Z_i}$ is a list of additional control variables. (Absolute systematic variation, $\ln(\sigma^2_{m,i})$, as we explain below, is appropriately considered a control variable too.)

We run alternative empirical specifications substituting the squared deviation of marginal q from one, $(\dot{q}-1)^2$ for the absolute deviation, $|\dot{q}-1|$ in [12]. Since the threshold optimum marginal q value may deviate from one because of taxes, we repeat these analyses substituting a tax adjusted threshold for one. That is, we estimate

$$
\begin{aligned}
&|\dot{q}_i - h| = b_\Psi \Psi + \mathbf{c}' \cdot \mathbf{Z_i} + u_i \\
&|\dot{q}_i - h| = b_\varepsilon \ln(\sigma^2_{\varepsilon,i}) + b_m \ln(\sigma^2_{m,i}) + \mathbf{c}' \cdot \mathbf{Z_i} + u_i
\end{aligned}
\qquad [13]
$$

and analogous regressions of $(\dot{q} - h)^2$ while allowing the data to estimate h as well as the regression coefficients.

This empirical framework is designed to minimize econometric problems. First, using marginal q ratios to gauge the values of firms' marginal capital budgeting projects is simple and direct. Estimating net-present values using accounting data is less direct, more cumbersome, and problematic because accounting data may not fully reflect the information utilized by either shareholders or managers. Second, to mitigate endogeneity problems, we use capital budgeting quality variables based on 1993 through 1997 data and lagged values (predetermined and historical) of firm-specific stock return variation based on 1990 through 1992 data. It turns out that using contemporaneous data does not materially affect our results. We describe such results in our robustness discussions.

4.4 Control Variables

We require controls for underlying factors that affect the quality of capital budgeting *per se*, and for latent common factors related to both capital budgeting quality and firm-specific returns variation.

Controlling for underlying factors that affect the quality of capital budgeting *per se* is necessary because the general quality of capital budgeting decisions might be higher in some industries than in others for reasons that are exogenous in our context. 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 industry characteristic obscures the true relationship between capital budgeting quality and firm-specific returns variation by causing heteroskedasticity in the regression errors. Thus, we include a measure of industry concentration to control for this effect in our capital budgeting quality measures.

Controlling for latent common factors related to both capital budgeting quality and firm-specific returns variation is necessary because, if our dependent and independent variables are both affected by a common latent variable, any correlation we observe between them might be due only to the latent variable. For example, concentrated industries, in addition to having better quality capital budgeting decisions, might also mainly 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 returns variation might simply reflect the effects of industry concentration on both variables. Including industry concentration as a control variable should remove this effect. In general, latent common factors measure industry characteristics that are unrelated to informed risk arbitrage, and that affect capital budgeting quality and that are also related to firm-specific fundamentals variation.

We therefore include as specialized control variables several such industry characteristics that might proxy for underlying factors or latent common factors of these sorts. However, the number of industry characteristics that might cause such problems is large, and our proxies may be imperfect. We can mitigate the problem of missing underlying factors by using heteroskedasticity consistent standard errors. Since latent common factors are variables related to firm-specific fundamentals variation, we deal with missing latent common variables by including proxies and direct estimates of firm-specific fundamentals variation itself.

Note that we do not include corporate governance variables, such as measures of 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 our Tobin's marginal *q* ratio variable. Including corporate governance variables would amount to putting proxies for our dependent variable on the right-hand side of our regressions. We are currently undertaking a separate research project to examine the importance of various corporate governance variables in the relationship between capital budgeting quality and firm-specific return variation, but this is outside the scope of the present paper.

The next two subsections describe these controls and our reasons for including each. These subsections can be skipped without loss of continuity, as a summary is presented in a final subsection.

4.4.1 Specialized Control Variables

We wish to control for *exogenous* industry characteristics that might affect the quality of capital budgeting decisions and that might be associated with firm-specific variation. This subsection describes variables designed to control for particular industry characteristics.

First, as argued above, industry concentration might matter. To control for this, we use a standard industry *Herfindahl Index*, denoted H_i, based on real sales averaged over 1990 to 1992.

Second, we ought to 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 consequently be more likely to exhibit the sorts of overinvestment problems discussed by Jensen (1986) than firms in smaller industries. Firms in smaller industries might be subject to greater information asymmetry problems, and so be more likely to ration capital and underinvest. Also, larger industries may be more mature, contain more homogenous firms, and so exhibit less firm-specific fundamentals variation. We therefore include the logarithm of the 1990-1992 average of the total value of property for each industry, denoted $\ln(K_i)$, as our *Industry Size* control variable. The estimation of K_i is explained in detail in the appendix equations [A6] and [A7].

Third, corporate diversification might matter. A large literature documents possible links between corporate diversification and both corporate governance problems and access to capital.[6] Also, corporate diversification might also reduce firm-specific fundamentals variation. Therefore, we control for the average level of diversification of firms whose core business is in industry *i*. To construct a proxy for firm diversification, we count the number of different 3-digit industry segments in which a firm operates in 1990-1992 according to the *Compustat Industry Segment Data Tape*. Our *Corporate Diversification* measure for industry *i*, denoted $segs_i$, is the

[6] 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 financial intermediary, investing surplus funds from one division in positive NPV projects in another, reducing the need for external funds. Amihud and Lev (1981), Morck et al. (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 (1997) argue that diversified firms shift income from cash rich divisions to cash poor ones out of a sense of "fairness". Rajan et al. (1998) propose that such transfers are due to self-interested divisional managers and weak head offices. Thus,

1990-1992 average of asset-weighted averages of firm level diversification for firms whose primary business is industry *i*.

Fourth, capital budgeting might be more error-prone in industries where intangible assets are important because the future cash flows they generate might be more difficult to evaluate *ex ante*. Moreover, firms in these industries typically have fewer assets that can serve as collateral for loans and bond issues and often have to rely more on internal capital, which might lead to capital rationing. Firms in intangible intensive industries might have more firm-specific variation in fundamentals. To control for the importance of intangibles, we include two control variables: industry *Research and Development Spending* (R&D) and industry *Advertising Spending*, denoted *r&d* and *adv* respectively. Both are measured per dollar of tangible assets in each industry measured across our 1990 to 1992 sample. Tangible assets are real property, plant and equipment and inventories, estimated as described in the Appendix. A firm's R&D or advertising is considered to be negligible if not reported and all other financial data are reported.

Fifth, general levels of liquidity might matter. This could affect capital budgeting decision. For example, firms with large cash hoards might overinvest, while those without such accumulations might employ capital rationing. To control for industry liquidity norms, we therefore use net current assets as a fraction of total assets for each industry averaged over 1990-1992. The denominator is real property, plant and equipment, estimated as described in the Appendix. We denote this industry *Liquidity* control variable λ_i.

Sixth, firms' existing capital structures may influence their capital budgeting decisions. 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

different levels of corporate diversification could conceivably generate a spurious correlation between financing decisions and stock return variation in several ways.

arguments constrain or distort capital budgeting decisions in highly leveraged firms. If higher leverage also affects fundamentals variation, such problems could bias our findings. We therefore include as an additional control variable each industry's average *Leverage*, lev_i, defined as the 1990-1992 average of net long-term debt over tangible assets. Our procedures for estimating long-term debt and tangible assets are described in the Appendix.

Seventh, the quality of capital budgeting decision may be affected by industry-specific factors, which the above controls do not fully capture. We therefore also include one-digit industry fixed effects.

We consider several other specific control variables in the robustness section below. Including these additional variables does not qualitatively change our findings.

4.4.2 Firm-specific Fundamentals Variation Control Variables

Above we considered a variety of industry characteristic that might affect our ability to estimate the true relationship between the quality of capital budgeting decisions and firm-specific stock return variation. Unfortunately, the number of industry characteristics that might matter is large, and many cannot be measured readily. We therefore include control variables that directly gauge the variation in firm-level fundamentals that is *not* associated with industry and market fundamentals variation. We first describe a proxy for firm-specific fundamentals variation that can be estimated precisely, and then describe direct estimates of firm-specific fundamentals variation that are likely to be estimated imprecisely.

It is plausible that firm-specific fundamentals variation should be larger in industries where systematic (market and industry-related) variation is also larger. This would be the case if, for example, firm-specific changes in fundamental value were larger and more frequent in industries where changes in market and industry-related fundamentals are larger and more frequent. Roll (1988) associates firm-specific variation with activity by arbitrageurs possessing private information, but allows that market and industry-related variation might more often reflect the capitalization of publicly announced information into share prices. If so, observed systematic variation might be a useful proxy for (unobserved) firm-specific fundamentals variation.

We therefore use our absolute systematic return variation measure, $\ln(\sigma_m^2)$, as a control variable in regressions explaining absolute firm-specific return variation, $\ln(\sigma_\varepsilon^2)$. We tentatively interpret it 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 explaining absolute firm-specific return variation, but not in regressions explaining relative firm-specific return variation.

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

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

$$ROA_{i,j,t} = \beta_{j,0} + \beta_{j,m} ROA_{m,t} + \beta_{j,i} ROA_{i,t} + \varepsilon_{i,j,t} \quad [14]$$

for each firm *j* in each industry *i* with *t* an annual time index. $ROA_{i,j,t}$ is firm *j*'s *ROA*, $ROA_{m,t}$ is a value weighted *ROA* index for the market, and $ROA_{i,t}$ is a value weighted industry *ROA* index. Again, we calculate $ROA_{i,t}$ as the average return across all other firms in the industry (or the market) except the firm in question. We run these regressions on our 1983 to 1992 sample of nonfinancial firms, which is 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

$${}_{ROA}R_i^2 = \frac{{}_{ROA}\sigma_{m,i}^2}{{}_{ROA}\sigma_{\varepsilon,i}^2 + {}_{ROA}\sigma_{m,i}^2}, \quad [15]$$

where

$$\begin{aligned} {}_{ROA}\sigma_{\varepsilon,i}^2 &= \frac{\sum_{j\in i} SSR_{i,j}}{\sum_{j\in i} T_j} \\ {}_{ROA}\sigma_{m,i}^2 &= \frac{\sum_{j\in i} SSM_{i,j}}{\sum_{j\in i} T_j} \end{aligned} \quad [16]$$

where $SSR_{i,j}$ and $SSM_{i,j}$ are now the unexplained and explained variations respectively of regression [14] 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, $\ln({}_{ROA}\sigma^2_{\varepsilon,i})$, our *absolute systematic fundamentals variation* measure, $\ln({}_{ROA}\sigma^2_{m,i})$, and our *relative firm-specific fundamentals variation* measure

$$_{ROA}\Psi_i = \ln\left(\frac{1-{}_{ROA}R_i^2}{{}_{ROA}R_i^2}\right) = \ln({}_{ROA}\sigma^2_{\varepsilon,i}) - \ln({}_{ROA}\sigma^2_{m,i}) \qquad [17]$$

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

Since we use annual data to estimate these direct measures of firm-specific fundamentals variation, and we have at most ten years of data for each firm, the resulting variance decomposition estimates are likely to be quite imprecise. Requiring more years risks cutting down the number of firms we can use in each industry, and risks making the fundamentals variation measures reflective of earlier conditions that no longer prevail in some industries. Using quarterly data is unlikely to be useful because quarterly financial data is unaudited and is considered less reliable than annual data.

We employ alternative ways of constructing these variables as robustness checks, described below. Our results are qualitatively unaffected by these changes.

4.4.3 Summary

In summary, we include control variables that capture various industry characteristics that might plausibly affect the quality of capital budgeting and that might be associated with firm-specific variation in fundamental values. These are: an industry Herfindahl index, a measure of industry size, the average level of diversification of firms whose core business is in each industry, measures of the importance of intangibles (R&D and advertising) in each industry, average liquidity, average leverage, and broader (one-digit) industry fixed effects.

We also include as a control variable absolute systematic return variation, $\ln(\sigma^2_{m,i})$, which we argue is a rough proxy for firm-specific fundamentals variation that can be estimated precisely; and direct estimates of firm-specific fundamentals variation that are likely to be estimated imprecisely. The latter include absolute firm-specific fundamentals (ROA) variation, $\ln({}_{ROA}\sigma^2_{\varepsilon,i})$, absolute systematic fundamentals variation, $\ln({}_{ROA}\sigma^2_{m,i})$, and relative firm-specific fundamentals variation, ${}_{ROA}\Psi_i$.

Univariate statistics for all of these control variables are presented in the bottom panel of Table 2, and their correlations with our capital budgeting quality measures are presented in the bottom panel of Table 3a. Table 3b presents the correlations of the control variables with each other, with the marginal *q*, and the deviation of marginal q from 1. The absolute value deviation of marginal *q* from 1 is positively correlated with industry size and negatively with liquidity. 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.

5. Main Regression Results

Table 4 presents regressions of the distance of marginal *q* from one on our firm-specific stock price variation variables and the control variables discussed above. The central result in Table 4 is that higher firm-specific stock return variation is statistically significantly associated with marginal *q* being closer to 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 it is also true regardless of whether the controls are included or not.

Overall, these finding are consistent with greater firm-specific stock return variation being associated with a higher quality capital budgeting.

6. Robustness of the Regression Results

In this section, we show that the central results described in the previous section are highly robust. Our robustness checks include residual diagnostic tests, re-examination of the dependent variable, variations in the construction of the control variables, inclusion of additional controls, and alternative empirical specifications. These changes qualitatively alter neither our findings nor our interpretation of them. By this we mean that, although the magnitudes of some coefficients and standard errors may change, and some control variables may gain or lose statistical significance, the signs and significance patterns of our stock return variation variables, $\ln(\sigma_\varepsilon^2)$ and Ψ_i, do not change. That is, the relationships between firm-specific stock return variation and the quality of capital budgeting decision remains significantly positive.

6.1 Residual diagnostic check

To safeguard against heteroskedasticity due to missing variables or general specification problems we use Newey-West standard errors to calculate the t-statistics. We also perform several tests to detect outliers. First, we apply Hadi's (1992, 1994) method, with a five percent cut-off, and detect no outliers. Second, we use critical a value of one for Cook's D statistics, and this also indicates no significant outlier problems. Finally, we trim the extreme values by dropping top and bottom 5% of the sample of our main variables. Although this reduces the sample size, it does not change our findings qualitatively.

6.2 Issues Regarding the Quality of Capital Budgeting Variables

A number of issues arise in connection with our use of marginal Tobin's q ratios as the dependent variable.

6.2.1 Taxes and Marginal *q*

One criticism of the results in Table 4 is that the threshold value of marginal q may not be one. Taxes and other effects can lead to a threshold value of marginal q lower than one. Investors' return from the firm plowing back a dollar of after-tax income into capital investment is $\dot{q}(1+D)(1-T_{CG})$ where D is the value of the depreciation tax shield generated and T_{CG} is the capital gains tax the investors pay upon selling the stock. For capital investment to make sense, this must be larger than the value to the investor if the firm paying out a dollar in dividends (or buying back a dollar's worth of outstanding securities). Taking capital structure as given, the value of the latter is $(1-T_{DIV})$ where T_{DIV} is the personal tax on dividends. The value of the former is $(1-T_{CG})$. This comparison is complicated by issues such as the tax favored status of interest payouts, timing of capital gains realization, depreciation tax rules, and the fact that some investors are tax free while other face a variety of marginal rates. Reasonable figures for the 1990s are T_{DIV} in the 33% to 39.6% range, T_{CG} equal to 28%, the present value of the depreciation tax shield equal to 23% of the value of capital invested, and repurchases equal to 20% of disbursement (Fama and French, 2000). These imply a threshold marginal q in the general neighborhood of 0.8.

We therefore re-estimate Table 4 using the deviation of marginal q from an endogenously determined threshold level h, which we estimate using nonlinear least squares.[7] Depending on specification, the estimated value of h ranges from 0.719 to 0.808 and it is significant in all specification. These results are shown in Table 5.

Moreover, since tax effects differ across industries, the tax-adjusted threshold marginal q might be industry-specific. Thus, the inclusion of one-digit industry dummies may already capture such effects to some extent. Our results are qualitatively similar if we include two-digit industry dummies, and if we exclude the industry dummies altogether.

6.2.2. Investment in Intangible Assets

Our measure of capital expenditure should perhaps include more than just spending on property, plant and equipment. Spending on intangible assets, such R&D and advertising, is also arguably a form of investment despite the fact that generally accepted accounting principles do not recognize it as such. We can modify [9], [10], and [11] by adding spending on R&D and advertising to ordinary capital expenditures in the estimation of $\dot{q}$.[8] Doing so does not change our results qualitatively.

6.2.3 Asset Depreciation Rates and Marginal *q*

In estimating marginal q ratios by running equation [11], we make use of total fixed capital, denoted $A_{i,j,t}$, as a scaling factor. Equation [A7] in the Appendix shows how this variable is estimated recursively by constructing an age profile of each firm's capital based on past

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[7] A complete discussion of nonlinear least squares estimation technique can be found in Amemiya (1985).

[8] 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% annual depreciation rate on both types of intangible investment to do this.

reported capital expenditure. After applying a 10% economic depreciation rate to this capital, we adjust the value of each tranche for inflation. We then add up these inflation adjusted values to obtain $A_{i,j,t}$,. An alternative approach is to take accounting depreciation as an approximation of true economic depreciation, as shown in equation [A13] of the Appendix. Re-estimating all our marginal q ratios using this alternative approach generates qualitatively similar results to those shown.

6.2.4 Discontinuous Marginal Investment Schedules

The normative statement that a firm should stop investing when its marginal capital budgeting project has an NPV of zero (a marginal q of one) presumes a continuous schedule of available investment projects with steadily decreasing NPVs. This may not describe the situation in firms that must undertake large discrete projects. In such a firm, that last inframarginal project may have a highly positive NPV while the marginal project has a large negative NPV. Undertaking all positive NPV projects and no negative NPV ones would leave this firm with a positive estimated NPV and an estimated marginal q ratio above one, but this does not indicate under-investment. Undertaking the next best available project would in fact constitute over-investment.

Most of the firms in our sample do not appear to be in such a situation, as the average marginal q ratio reported in Table 2 is 0.69, and is statistically significantly below one (prob-value = 0.00) and also below 0.8 (the estimated value of h, the "optimal" of marginal q as in eq. 13) (the prob-value is 0.05). Moreover, the marginal q ratios for 121 of our 214 industries are below one. A high marginal q can indicate either underinvestment due to poor capital budgeting or a lumpy investment schedule, but a low marginal q unambiguously indicates overinvestment.

We can exclude the problem of discontinuous investment schedules by dropping industries with estimated marginal q ratios above one. In the remaining industries, we find that high firm-specific return variation is associated with higher marginal q ratios, (that is, with marginal q ratios closer to one). We obtained similar results when we drop industries with estimated marginal q ratios above 0.8, the estimated "optimal" value of q as in Eq. 13.

6.2.5 Discontinuous Costs of Capital

Firms subject to liquidity constraints can exhibit behavior similar to those confronting discontinuous investment schedules. For example, despite having a large range of projects with positive NPVs evaluated at its internal cost of capital, a firm might only undertake a few projects because its internal funds are limited. Raising further funds would require accessing outside financing at a higher cost, and at this higher cost of capital, the remaining projects have negative NPVs. Again, this allows the marginal project to have a negative NPV even though the last (observed) inframarginal project has a positive NPV.

If this situation describes our high marginal q firms, there should be a positive relationship between measures of the strength of liquidity constraints and marginal q across high marginal q industries, but not necessarily any relationship between firm-specific return variation and marginal q unless our firm-specific variation measures are somehow proxying for liquidity constraints.

To investigate this, we re-estimate Table 5 for the $\dot{q} > 0.80$ subsample of industries, but include as controls not only our basic liquidity measure (λ, which is equal to net current assets over total assets for 1990 to 1992), but also additional liquidity variables, cash flow over total assets and past external financing activity, both defined over 1990 to 1992 and both constructed as described in section A3 of the Appendix.

We find that the firm-specific stock return variation is negatively and significantly related to marginal q in the high marginal q sub-sample. This is true regardless of whether what combination or subset of the three liquidity variables we use.

We conclude that, while such liquidity constraints may be important, they are not solely responsible for our main findings.

6.2.6 Noisy Stock Prices and Marginal *q*

Finally, we estimate marginal q, by running regressions that explain current changes in firm market value, as in [11]. If stock prices contain noise (which we observe as high firm-specific stock return variation), this noise could cause our marginal q estimates to deviate from their "true" value as assessed by investors. This could create a spurious positive correlation between firm-specific return variation and the deviation of marginal q from its optimal value.

However, we observe higher firm-specific return variation associated with marginal q ratios closer to one. That is, noise of this sort should bias our tests against finding the results we obtain.

6.2.7 Shareholder Value or Firm Value?

Our marginal q estimated is the change in firm value (equity plus debt) associated with a marginal increase in capital assets. An alternative approach is to estimate a marginal equity q ratio, the change in shareholder value associated with a marginal increase in capital assets. While the latter approach superficially corresponds to our focus on stock returns variation rather than value variation, we believe using the change in firm value is the better methodology. This is because events that affect firms' costs of and access to debt financing also affect their share prices.

Nonetheless, we repeat our regressions using an alternative marginal *q* ratio based on shareholder value alone. The results are qualitatively similar to those shown in the tables. Consequently, we are unable to shed light on conflicts between shareholders and bond holders. This may be because our marginal q estimates are for industries rather than firms, and no entire industry in our sample period verged on bankruptcy, the threat of which galvanizes conflicts between shareholders and bondholders.

6.3 Other Control Variables

We now return to our list of control variables. We consider alternative constructions for our basic control variables as well as additional control variables. We find that these changes do not qualitatively alter our basic findings. The information included in this sub-section can be omitted without loss of continuity.

6.3.1 Alternative Specialized Control Variables

First, we can control for industry competitive structure with Herfindahl index based on firm assets or employees, rather than sales. These alternative competitive pressure indices lead to results qualitatively similar to those shown.

Second, we can control for industry size in various ways. In Tables 4 and 5, we use the natural logarithm of total fixed capital, as estimated using equation [A7] in the Appendix. This procedure assumes a 10% depreciation rate on all property, plant and equipment. We can re-estimate total fixed assets using equation [A13] instead, which used reported income-statement depreciation instead. As yet another measure of industry size, we use the logarithms of 1990 to 1992 average total book assets or number of employees. All of these alternative size measures generate qualitatively similar results to those shown.

In discussing possible problems with our capital budgeting quality measures above, we introduced two additional liquidity measures, cash flow over assets and past use of external financing (both described in detail in section A3 of the Appendix). Substituting either of these alternative liquidity measures for our basic liquidity variable generates qualitatively similar results. So does including all three together.

Our regressions in Table 4 include one-digit industry fixed effects. Using two-digit fixed effects instead generates qualitatively similar results, and the 59 two-digit dummies are mostly insignificant.

6.3.2 Alternative Firm-specific Fundamentals Variation Control Variables

We can substitute variants of our basic fundamentals co-movement variables and generate qualitatively similar results.

We use [A7] to adjust the denominator of *ROA* for inflation. Constructing *ROA* entirely from book values generates the same pattern of signs and significance, as does adjusting PP&E with reported depreciation, as in [A13].

Dropping observations where $|ROA_{i,j,t} - ROA_{i,j,t-1}| > 25\%$ to avoid spurs in accounting *ROA* caused not by changes in real fundamentals, but by transitory extraordinary events and tax saving practices, eliminates 17 firms 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*), equal to 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 fundamental 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 firms' fundamentals are, 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.

6.3.3 Additional Control Variables

Several other industry characteristics are worthy of mention.

Some industries are more exposed to pressure from foreign trade competitive than are others. Movement toward free trade due to NAFTA and the WTO might subject these industries to intensified competitive pressure. This pressure might, in turn, improve the quality of capital budgeting decisions in such exposed industries. We therefore included as an additional control variable industry exports minus imports over industry sales.[9] This does not qualitatively change our findings. Including industry capital-labor ratios, which are indirect measures of comparative advantage, also fails to qualitatively alter our results.[10]

Arguably, firm size might be as important as industry size. Although the dominance of particularly large firms is already captured by our Herfindahl indices, we can include further controls. We therefore include as additional independent variables several alternative measures of the *average* firm size in each industry. These are the logarithms of 1990 to 1992 average real firm assets estimated using [A7], average real assets estimated using [A13], book assets, real sales, and employees. Adding these variables, individually or together, does not qualitatively change our results.

It may be intrinsically more difficult to predict the future in rapidly growing industries, such as high-technology sectors. Also, information asymmetry between managers and investors is conceivable greater in such industries. These complications could affect the market's assessment of the quality of firms' capital budgeting decisions. If stock return variation is also different in such industries, this could bias our results. To take account of this possibility, we repeat our Table 4 regressions using only the industries that report zero R&D spending, assuming that R&D spending can proxy for expected future growth option value. We obtain results qualitatively similar to those shown in Table 4.

A final possibility is that, since Table 3a shows high firm-specific variation accompanying high systematic variation, the cost of equity capital is higher when firm-specific variation is higher. However, all our regressions either scale firm-specific risk by systematic

[9] 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.
[10] Capital-labor ratios are deviations from the economy-wide weighted average.

risk, as in Ψ, or include systematic risk as a control variable, $\ln(\sigma_m^2)$. This seems adequate because, when we divide industries into above- and below-median Ψ, the two resulting returns distributions are statistically identical, indicating similar 'cost of equity' distributions.[11] Nonetheless, we can control for the cost of equity capital directly. Explicitly including 1990 to 1992 industry-average equity returns or equity betas generates qualitatively similar findings to those shown in Table 4. So does including 1990 to 1992 industry-average weighted average costs of capital or unlevered betas.[12]

6.4 Alternative Specifications

Our results are also robust to various changes in the specification.

First, we use 1990 to 1992 data to construct our stock return variation measures and 1993 to 1997 data to construct our marginal q estimates. This is to mitigate possible endogeneity problems and because the consequences of investment decisions may not become obvious to shareholders for several years. Using contemporaneous marginal q and return variation measures, constructed with data from either of these periods, generates qualitatively similar results.

Second, non-optimal marginal q ratios can be either too high or too low. It is of interest to see whether one or both types of nonoptimality are important. Repeating our correlations and regressions using only industries with marginal q less than one (121 observations) generates qualitatively results consistent with those shown. Higher firm-specific return variation is associated with higher marginal q. For the marginal $q > 1$ sample (93 observations), both $\ln(\sigma_\varepsilon^2)$

[11] For the 1990 to 1992 period, Kolmogorov-Smirnov D-statistic for rejecting identical distributions is 0.106 (p-value = 0.74). For the 1993-97 period, the D-statistic is 0.241 (p-value = 0.62).

and Ψ are statistically insignificant but retain signs consistent with higher firm-specific variation being linked to lower marginal q. We are concerned that this insignificance may be due to the smaller sample size. When we repeat the analyses using marginal q = 0.80 as the dividing line between the high and low marginal q subsamples, we find significant relationships in both subsamples consistent with those shown in the tables. Higher $\ln(\sigma_\varepsilon^2)$ and Ψ are linked with lower marginal q in the marginal q > 0.80 subsample (116 observations), and with higher marginal q in the marginal q < 0.80 subsample (98 observations). Although we recognize the econometric problems associated with using the dependent variable to censor the sample, these results support the reliability of our main results.

Third, the regressions in Table 4 should not work if we use marginal q itself, rather than its deviation from one, or 0.80, as the dependent variable. When we run $\dot{q}$ on the independent variables in Table 4 across the full sample of industries, we obtain insignificant coefficients on our firm-specific stock return variation variables.

Finally, studies of corporate investment often consider average Tobin's q, rather than marginal q, since average q measures total, rather than marginal, market value added. Average q is the total market value of the firm, $V_{j,t}$, over the total replacement cost of all the firm's assets, $A_{j,t}$, which we denote

$$\overline{q}_{j,t} \equiv \frac{V_{j,t}}{A_{j,t}}, \qquad [18]$$

As a firm invests in ever more marginally value-increasing projects, its marginal q falls to one. Its average q, however, need not fall to one, for the firm's average q is investors' expected present value of cash flows from its marginal *and inframarginal* capital investments; all scaled

[12] We are grateful to seminar participants at the University of North Carolina at Chapel Hill and at Indiana University for stressing this point and suggesting these robustness checks.

by the sum of the replacement costs of the assets associated with those investments. Thus, all else equal and in the absence of liquidity constraints, a high average q ratio signifies a history of *ex post* value-creating investments. If higher firm-specific stock return variation is associated with a long history of value creating investment decisions, a positive relationship between average q and firm-specific stock return variation should be evident.

To estimate an industry's average 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 take an average for each industry from 1993 through 1997. Although average q is uncorrelated with marginal q and negatively correlated with marginal q's deviation from one, it is positively significantly related to all five measures of the use of external financing. Regressions analogous to those in Table 4, but with average q as the dependent variable, show both absolute and relative firm-specific return variation, measured by $\ln(\sigma_\varepsilon^2)$ and Ψ, to be positively and significantly related to the value of average q. Also, in these regressions, as well as simple correlation tests, systematic variation, $\ln(\sigma_m^2)$, is uncorrelated with average q.

These average q results survive the above mentioned robustness checks for Table 4. For example, using alternative liquidity controls such as net current assets over total assets, cash flow over total assets, and past external financing activity generate qualitatively similar results. Since average q estimates are simple ratios, rather than regression coefficient like our marginal q estimates, we can run firm-level average q regressions. These generate qualitatively similar results. Using value to sales ratios instead of average q also generates qualitatively similar results, as does using contemporaneous dependent and independent variables rather than lagging the latter.

6.5 Summary

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 more consistent with value maximization.

7. Discussion

Our results indicate that capital budgeting is more aligned with market value maximization in industries where firm-specific stock return variation is higher. This finding is highly statistically significant and robust.

7.1 Economic Significance

Our results are highly economically significant. In regression 4.5, a one standard deviation increase in absolute firm-specific stock return variation, $\ln(\sigma_{\varepsilon}^{2})$, reduces $|\dot{q}-1|$ by 0.174×0.859 or 0.149, roughly 31% 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 16%. The improvements, when measured by the squared distances of marginal q from one, are 74% and 30%, respectively.

7.2 The Information Content of Stock Prices

We feel that the simplest interpretation of our result is that capital budgeting is more aligned with share value maximization in industries where firm specific returns variation is higher because share prices are more informed in those industries. More informed share prices allow corporate governance mechanisms to work better, so that non-value-maximizing managers are reigned in or removed quickly. More informed share prices mean information asymmetry problems are reduced, so that firms are better able to undertake all available positive NPV projects (and no negative NPV ones). More informed stock prices mean investors and managers more closely agree as to what decisions constitute optimal capital budgeting.

Since marginal q ratios are both above and below, but predominantly below, the theoretical optimum, our results can be driven neither by lumpiness in capital investments nor by binding liquidity constraints. Consequently, our results suggest that agency problems, especially those that lead to overinvestment such as Jensen's (1986) free cash flow theory or Roll's (1988) Hubris hypothesis, must become more important when share prices are less informed. This is consistent with our observation that the proper functioning of corporate governance mechanisms depends on the information contained in share prices.

This interpretation is consistent with the conclusions of Durnev *et al.* (2001) that stock price asynchronicity is a measure of the information content of stock prices, as defined by Lev and Ramu (1993), Collins and Kothari (1989), and others. It is also consistent with the use of stock returns asynchronicity as a measure of informed trading by Morck *et al.* (2000) and Wurgler (2000). Finally, it buttresses contention of French and Roll (1986) and Roll (1988) that firm-specific returns variation reflects the incorporation of private information into share prices by informed risk arbitrageurs.

Indeed, our results not only suggest that firm-specific variation is a characteristic of an efficient market, but that higher firm specific risk may actually be associated with more informed stock prices. If higher firm specific stock returns do indeed indicate a higher information content, this implies that capital allocation is more in accordance with shareholders perceptions of their own interests when share prices are more informed. In short, the stock market may be more functionally efficient, in the sense of Tobin (1982), for higher Ψ stocks.

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 et al. (2000) and Wurgler (2000) stress differences in institutional environments across countries, such as the varying levels of public sectors corruption and investor protection, and different legal systems. Obviously, all firms in the US are subject to the same legal, regulatory and institutional environment. Institutional differences may explain cross-country differences in stock return synchronicity, but cross-industry differences within the US must be due to other factors.

7.3 Noisy Stock Prices – A Caveat

It is important to underscore that our Tobin's marginal q ratios measure *shareholders' perceptions about the quality of capital investment*. If higher firm-specific stock returns variation does indeed indicate that shareholders are less well informed or subject to worse fits of frenzy, their perceptions may be in error. Thus, while it is tempting to equate marginal q ratios farther from one, or the tax adjusted optimum, with economically inefficient capital budgeting, we can not rule out the possibility that managers might be more informed than shareholders, and that marginal q's deviating from their theoretical optima might reflect managers maximizing fundamental firm values. If this is so, a closer alignment of capital budgeting to shareholders perceptions of optimality would decrease, rather than increase the microeconomic efficiency of capital allocation.

Since marginal q deviations are larger in industries with lower firm-specific returns variation, this interpretation requires that low firm-specific variation be associated with share prices deviating further from fundamentals. It therefore leads to the same ultimate conclusion – higher firm-specific variation cannot be indicative of greater errors in asset pricing, but rather reflects informed trading.

7.4 Incomplete Risk 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 far from certain of the validity of this explanation, and welcome other explanations of our findings.

Our speculation all turns on the possibility that risk arbitrage might be more complete in industries where stock returns are less synchronous. Shleifer and Vishny (1997) and Shleifer (2000, chapter 4) argue that arbitrage activity is limited by arbitrageurs' risk aversion and by the cost of obtaining and analyzing the information needed to estimate fundamental values. 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 will 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 risk arbitrage might be more severely limited in some industries than in others. In the next subsection, we consider some specific ways in which this might happen. First, this might occur because some industries are inherently more opaque to outside investors than others. Second, this situation might also arise because managers can better divert shareholders' earnings to themselves in some industries. Third, such differences might arise because noise traders are more active in some industries than others. Our speculations are based on these three possibilities, however we readily invite other explanations.

7.4.1 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 than those of firms in other industries. If so, arbitrage limits might more severely curtail firm-specific arbitrage plays than market or industry plays, where holding period risk is partly diversified away. Since French and Roll (1986) and Roll (1988) find firm-specific stock price fluctuations mainly to reflect private information being incorporated into prices by informed arbitrageurs' trading, an absence of arbitrage on firm-specific information might be evident as depressed firm-specific returns variation – at least over short intervals.

Over long intervals, 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 of the price finally moves to its fundamental value. That is, uncapitalized firm-specific information is "built up and discharged". This capacitance view of information capitalization implies that our measured differences in firm-specific returns 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 are reduced and the statistical significance of these variables in the regressions fall, though their signs do not change. A ten-year window is sufficient to render all their coefficients statistically insignificant. Unfortunately, this might also merely reflect the greater use of stale return variation data in estimating these variables over longer windows, and so cannot be taken as clear confirmation of this explanation. We are pursuing this avenue of investigation 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 uncapitalized information build-up. Such 'depreciation' in the value of private information would mean that 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 thus pass into irrelevance without ever being capitalized into share prices.

If this 'depreciation of firm-specific information' 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.

7.4.2 Agency Problems and Firm-specific Arbitrage

A second closely related possibility is that management might more readily appropriate earnings, rather than pay earnings out as dividends, in some industries than in others. If management appropriates abnormally high earnings due to abnormally high market-wide or industry-wide earnings, this is obvious to shareholders unless all other managers do likewise. However, if management appropriates abnormally high firm-specific earnings, shareholders may never know of this. Arbitrageurs might, however, come to rationally expect such appropriations, and thus view predicting firm-specific fundamentals changes as of little value. Consequently, firm-specific returns variation is depressed, there is little variation across firms in the industry in fundamental returns from shareholders' perspective, and our earnings-based fundamentals co-movement variables may not capture this.

If insiders' misappropriation raises operating costs, we should see a corresponding effect on firm-specific fundamentals variation, ${}_{ROA}\sigma_{\varepsilon}^{2}$. Since ${}_{ROA}\sigma_{\varepsilon}^{2}$ should control for such an effect in Tables 4 and 5, this story depends on the inadequacy of our controls for fundamentals variation decomposition. However, it is also possible that insiders' misappropriations reduce the linkage between earnings and dividends without increasing operating costs. If so, earnings variation might be unaffected, with shareholders merely doubting that high firm-specific earnings would ever translate into high firm-specific future dividends. This effect might, however, be distinguishable as a negative skewness in the firm-specific components of individual stock returns, for insiders would tend to appropriate positive firm-specific returns, but not negative ones. We are pursuing this possibility elsewhere.

7.4.3 Noise Traders and Firm-specific Arbitrage

A third possibility is that noise traders concentrate their trading in certain 'fad' industries. Black (1988) 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 are not always immediately dampened by arbitrageurs, and argue that this is especially likely when noise traders' mispricing errors are systematic. They consequently propose that noise trading induces market-wide returns 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 arbitrageurs must bear, and so deters risk arbitrage. As explained in 7.2.1, this could lower our measured values of $\ln(\sigma_\varepsilon^2)$ and Ψ.

However, this interpretation would seem inconsistent 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, $\ln(\sigma_\varepsilon^2)$, in many 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.

7.5 Qualifications

In our Table 4 and 5 regressions, we attempt to control for fundamental return variation decomposition as thoroughly as we can. However, we recognize that our controls are imperfect. Consequently, we also cannot categorically reject the possibility that our results might be driven by a relationship between firm-specific fundamentals variation, proxied for by $\ln(\sigma_\varepsilon^2)$ or Ψ, and the quality of capital budgeting decisions.

Finally, 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.

8. Conclusions

Our main finding is capital budgeting policies more closely approximate market value maximization in industries where stocks exhibit greater firm-specific return variation. That is, we find fewer marginal q ratios far above and far below its theoretical optimal value in industries exhibiting higher firm-specific stock return variation. This finding is highly statistically and economically significant. It is quite 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) finds that common asset pricing models have low R^2 statistics, and attributes this to high levels of firm-specific return variation. He further shows that this firm-specific variation is not associated with public information releases, and concludes (p. 56) that it reflects "either private information or else occasional frenzy unrelated to concrete information." Our findings are inconsistent with firm-specific returns variation reflecting investor frenzy. Moreover, not only do our results imply that firm-specific returns variation is due to informed arbitrageurs' trading, they suggest that share prices might actually be closer to fundamental values where firm-specific returns variation is higher! One possibility is that activity by informed arbitrageurs reduces noise trader induced errors in share prices, as predicted by De Long *et al.* (1989).

Second, the extent to which corporate capital budgeting decisions maximize firm value is a crucial issue in finance. Managers may fail to make capital budgeting decisions that maximize firm value because of corporate governance problems associated with managerial self-interest, ignorance, or incompetence. Sub-optimal capital budgeting decision 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, we find marginal *q*s both above and below the theoretical optimum, but predominantly the latter, where firm-specific variation is small. Our results therefore cannot be solely due to lumpiness in investment schedules or underinvestment due to liquidity constraints, for these would lead to excessively high marginal *q*s. Agency problems, which can lead to overinvestment and hence excessively low marginal *q*s, must thus be worse where firm-specific returns variation is low. If higher firm specific returns variation does indeed indicate more informed stock prices, this is consistent with corporate governance mechanisms working better where share prices are more informed.

Fourth, our interpretation of our results suggests that the US stock prices track fundamental values with differing degrees of accuracy in different industries. How is this possible? We speculate that such differences might arise because informed risk 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 difference 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.

Fifth, if we follow Tobin (1982) and defines 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 returns 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 the above interpretation of our findings to be sound, we recognize that this work is preliminary and welcome other explanations of our finding that greater firm-specific returns variation coincides with marginal Tobin's q ratios closer to optimal values.

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Appendix

A1. Construction of the Datasets

Our sample begins with all companies listed in CRSP from 1990 to 1992. We discard duplicate entries for preferred stock, class B stock, and the like by deleting entries whose CUSIP identifiers CRSP appends a number other than 10. We match these companies with those listed in Standard and Poor's annual COMPUSTAT tapes, and delete four firms that report negative sales. Because CRSP and COMPUSTAT occasionally assign the same firm different CUSIP identifiers, we visually inspected the lists of unmatched firms in both. Where company name matches (or near matches) are evident, we check the CRSP permanent identification number, ticker symbols and stock prices to reject false matches. This matching procedure adds 165 firms to our firm-level full sample, leaving 6 firms listed in COMPUSTAT but not CRSP and 14 firms in CRSP but not COMPUSTAT. We discard these.

Since the analysis below requires more than one firm in each industry in constructing the firm-specific stock return variables, we drop seven industries that contain three or fewer firms. Since accounting variables for financial and banking industries (SIC codes from 6000 through 6999) are not comparable to those of non-financial industries we exclude the former. Regulated utilities (SIC 4900 through 4999) are arguably subject to different investment constraints than unregulated firms, though liberalization in the 1980s may have mitigated this difference to some extend. Although we leave utilities in our sample of industries, dropping them does not qualitatively change our results.

Finally, we drop firm-year observations with fewer than thirty days of daily stock returns data. When firms are delisted and COMPUSTAT indicates that a bankruptcy occurred, we assume a final daily return of minus 100%. 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 6,021 firms spanning 214 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 prior to 1993. For these, we expand the 1990 to 1992 sample backward to *1983* by keeping sample firms that remain listed in COMPUSTAT in the period demarcated by those years. This '*1983 to 1992 sample*' contains 5,680 firms spanning 214 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 6,375 firms spanning 214 three-digit industries. (The length of this window is arbitrary; our results remain using 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 those 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 database. Firms need not have data for all time periods to be included in any of the samples; so all are unbalanced panels.

A2. Marginal Tobin's *q* Estimation Procedure

We consider 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

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

where $\hat{r}_{j,t}$ is the expected return from owning the firm, $\hat{d}_{j,t}$ its expected disbursement rate (including cash dividends, share repurchases, and interest expensive), $\hat{g}_{j,t}$ the expected rate of spending on capital goods, and $\hat{\delta}_{j,t}$ the expected depreciation rate on those capital goods.

Rewriting this, normalizing by $A_{j,t-1}$, we obtain

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

or

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

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

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

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

where

$CS_{j,t}$ = *the year t calendar year-end 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 property, plant and equipment.*

INV = *estimated market value of inventories.*

Before continuing, we provide details on the estimation of the market values of long-term debt, property, plant and equipment, 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 15 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 property, plant and equipment, $K_{j,t}$. 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 a 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.) *PP&E* in year *t-9* is then

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

More generally, we apply the recursive equation

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

Thus, PP&E in year t + 1 is PP&E from year t minus 10% 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[13].

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

$$\frac{\Delta V^i_{j,t}}{A^i_{j,t-1}} = \alpha^i + \beta^i_0 \frac{\Delta A^i_{j,t}}{A^i_{j,t-1}} + \beta^i_1 \frac{V^i_{j,t-1}}{A^i_{j,t-1}} + \beta^i_2 \frac{div^i_{j,t-1}}{A^i_{j,t-1}} + u^i_{j,t} \qquad [A8]$$

to obtain a marginal q estimate, $\dot{q}_i \cong \beta^i_0$, for that industry ($div^i_{j,t-1}$ is defined as dividends for common shares plus repurchases of common shares plus interest expenses).

[13] This index is available at http://www.stls.frb.org/fred/data/ppi/ppifgs.

Error terms are assumed to satisfy the following conditions: $u^i_{j,t}$ has zero mean, $\mathrm{cov}(u^i_{j,t}, u^i_{j,s}) \neq 0 \forall$ t and s; and $\mathrm{cov}(u^i_{j,t}, u^i_{k,t}) \neq 0 \forall j$ and k. Equation [16] is estimated in a firm-time random effects model. All variables are scaled by $A^i_{j,t-1}$ to mitigate heteroskedasticity problems.

A3. Additional Variables

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

$$\lambda_i = \frac{\sum_{j\in i, t\in[1990,1992]} current\ assets_{j,t} - current\ liabilities_{j,t}}{\sum_{j\in i, t\in[1990,1992]} tangible\ assets_{j,t}} \qquad \text{[A9]}$$

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

We define *cash flow over total assets* as

$$c_i = \frac{\sum_{j\in i, t\in[1990,1992]} income_{i,j,t} + depreciation_{i,j,t}}{\sum_{j\in i, t\in[1990,1992]} tangible\ assets_{i,j,t}} \qquad \text{[A10]}$$

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 property, plant and equipment, estimated using the recursive procedure in [A7], plus real inventory.

We define *leverage* as

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

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

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

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 debts and account 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, $D_{j,t}$, rather than the assumed 10% economic depreciation rate used in [A7]. The resulting recursive formula,

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

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

Table 1
Definitions of Main Variables

Variable		*Definition*
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 number of firm-year observations) from regressions of firm return on market and 3-digit industry value-weighted indices (constructed excluding own return) run on daily data by 3-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 number of firm-year observations) from the regressions described above.
Panel B. Quality of capital budgeting variables		
marginal q	$\dot{q}$	The coefficient in regression of unexpected change in firm value on unexpected change in tangible assets and controls by 3-digit industry using annual data from 1993 through 1997. Tangible assets is defined as the sum of real property, plant, 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 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 number of firm-year observations) from regressions of firm ROA on market and 3-digit industry value-weight ed ROA indices (constructed excluding own return) run on annual data by 3-digit industry from 1983 through 1992. ROA is the sum of income, interest expenses, and depreciation over tangible assets. Tangible assets is defined as above.
absolute systematic fundamentals variation	$\ln({}_{ROA}\sigma_{m}^{2})$	Logarithm of explained sum of squares (scaled by 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 number of firm-year observations) from the regressions described above.
corporate diversification	*segs*	Total assets weighted average number of 3-digit industries a firm operates in, 1990-1992 average.
Herfindahl index	*H*	Three-digit industry Herfindahl index constructed using sales data, average of indices from 1990 through 1992.
size	*ln(K)*	Log of average from 1990 through 1992 of real property, plant, and equipment, estimated using recursive formula in [A7].
liquidity	λ	The ratio of the difference between book values of current assets and current liabilities to tangible assets from 1990 through 1992. Tangible assets is defined as above.
leverage	*lev*	1990-1992 total book value of net long-term debt over total capital spending. This variable is truncated from 0 and 1.
advertising spending	*adv*	Total from 1990 through 1992 of inflation adjusted advertising expenditures over tangible assets. Tangible assets is defined as above.
R&D spending	*r&d*	Total from 1990 through 1992 of inflation adjusted R&D expenditures over tangible assets. Tangible assets is defined as above.

Table 2
Univariate Statistics for Main Variables

Variable		*mean*	*standard deviation*	*minimum*	*maximum*
Panel A. Stock return variation variables					
firm-specific stock return variation	σ^2_ε	0.032	0.043	0.013	0.418
systematic stock return variation	σ^2_m	0.008	0.107	0.001	0.094
systematic rel. to firm-specific stock return variation	R^2	0.211	0.087	0.040	0.566
absolute firm-specific stock return variation	$\ln(\sigma^2_\varepsilon)$	-3.854	0.859	-6.635	-0.871
absolute systematic stock return variation	$\ln(\sigma^2_m)$	-5.255	0.794	-7.418	-2.364
relative firm-specific stock return variation	Ψ	1.401	0.549	-0.265	3.184
Panel B. Quality of capital budgeting variables					
marginal *q*	$\dot{q}$	0.687	0.638	-2.454	2.676
squared deviation of marginal *q* from one	$(\dot{q}-1)^2$	0.405	1.035	0.000	11.935
absolute deviation of marginal *q* from one	$\lvert\dot{q}-1\rvert$	0.475	0.425	0.006	3.454
Panel C. Control variables					
absolute firm-specific fundamentals variation	$\ln({}_{ROA}\sigma^2_\varepsilon)$	-0.172	1.036	-5.470	1.918
absolute systematic fundamentals variation	$\ln({}_{ROA}\sigma^2_m)$	-0.411	1.076	-3.371	2.029
relative firm-specific fundamentals variation	${}_{ROA}\Psi$	0.239	0.722	-2.651	2.419
corporate diversification	*segs*	1.262	0.021	1.143	1.297
Herfindahl index	*H*	0.121	0.128	0.004	0.925
Size	ln(*K*)	8.357	1.907	3.701	13.87
Liquidity	$\tilde{\lambda}$	0.320	0.474	-2.701	2.309
Leverage	*lev*	0.697	0.313	0.000	1.230
advertising spending	*adv*	0.026	0.446	0.000	0.295
R&D spending	*r&d*	0.036	0.092	0.000	0.641

Note for Table 2. This table reports means, standard deviations, min, and max of main variables. Refer to Table 1 for variable definitions. Sample is 214 three-digit industries for all variables. Stock return variation measures (σ^2_ε, σ^2_m, R^2, $\ln(\sigma^2_\varepsilon)$, $\ln(\sigma^2_m)$, Ψ) are constructed using 1990-1992 data and based on a sample consisting of 214 three-digit industries (6,021 firms). Quality of capital budgeting variables ($(\dot{q}-1)^2$ and $\lvert\dot{q}-1\rvert$) are constructed using 1993-1997 data and based on a sample consisting of 214 three-digit industries (6,375 firms). (seg, H, ln(K), $\tilde{\lambda}$, lev, adv, r&d) sample is constructed using 1990-1992 data and consists of 214 three-digit industries based on 6,021 firms. $\ln({}_{ROA}\sigma^2_\varepsilon)$, $\ln({}_{ROA}\sigma^2_m)$, and ${}_{ROA}\Psi$ are constructed using 1983-1992 data and consists of 214 three-digit industries based on 5,680 firms. Finance industries (SIC code 6000 - 6999) are omitted.

Table 3a
Simple Correlation Coefficients of Capital Budgeting Quality and Firm-specific Stock Return Variation Variables with Each Other and with Control Variables

		$(\dot{q}-1)^2$	$\lvert\dot{q}-1\rvert$	$\ln(\sigma_\varepsilon^2)$	Ψ
Panel A: Quality of capital budgeting variables					
absolute deviation of marginal q from 1	$\lvert\dot{q}-1\rvert$	**0.888** (0.00)	-	**-0.135** (0.05)	**-0.131** (0.05)
Panel B: Firm-specific stock return variation variables					
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	**-0.157** (0.02)	-	-	**0.434** (0.00)
relative firm-specific stock return variation	Ψ	**-0.132** (0.05)	-	-	-
Panel C: Control variables					
absolute systematic return variation	$\ln(\sigma_m^2)$	-0.079 (0.24)	-0.088 (0.19)	**0.761** (0.00)	**-0.222** (0.00)
absolute firm-specific ROA variation	$\ln({}_{ROA}\sigma_\varepsilon^2)$	0.053 (0.44)	0.066 (0.33)	**0.363** (0.00)	**0.276** (0.00)
absolute systematic ROA variation	$\ln({}_{ROA}\sigma_m^2)$	0.006 (0.93)	0.048 (0.48)	**0.230** (0.00)	**0.194** (0.01)
relative firm-specific ROA variation	${}_{ROA}\Psi$	0.066 (0.33)	0.024 (0.72)	**0.182** (0.03)	**0.110** (0.10)
corporate diversification	*segs*	0.009 (0.90)	-0.067 (0.52)	**-0.101** (0.10)	**-0.120** (0.09)
Herfindahl index	*H*	0.024 (0.61)	0.013 (0.84)	**-0.219** (0.00)	-0.093 (0.16)
industry size	*ln*(*K*)	0.069 (0.30)	**0.156** (0.02)	**-0.243** (0.00)	-0.063 (0.35)
liquidity	λ	-0.046 (0.49)	**-0.110** (0.10)	0.090 (0.18)	0.031 (0.60)
leverage	*lev*	**-0.131** (0.05)	**-0.148** (0.03)	0.0800 (0.27)	0.0200 (0.74)
advertising spending	*adv*	0.062 (0.36)	0.037 (0.58)	**0.148** (0.03)	0.104 (0.13)
R&D spending	*r&d*	**0.109** (0.10)	0.038 (0.57)	0.0580 (0.40)	0.0620 (0.37)

Note for Table 3a. This table reports correlation coefficients. Quality of capital budgeting variables (($\dot{q}$ -1)^2 and |$\dot{q}$ -1|) are constructed using 1993-1997 data and based on a sample consisting of 214 three-digit industries (6,375 firms). Stock return variation measures ($\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, Ψ) are constructed using 1990-1992 data and based on a sample consisting of 214 three-digit industries (6,021 firms). (seg, H, ln(K), $\tilde{\lambda}$, lev, adv, r&d) sample is constructed using 1990-1992 data and consists of 214 three-digit industries based on 6,021 firms. $\ln({}_{ROA}\sigma_\varepsilon^2)$, $\ln({}_{ROA}\sigma_m^2)$, and ${}_{ROA}\Psi$ are constructed using 1983-1992 data and consists of 214 three-digit industries based on 5,680 firms. Finance industries (SIC code 6000 - 6999) are omitted. Refer to Table 1 for variable definitions. Correlation coefficients are based on 214 three-digit industries sample. Numbers in parentheses are probability levels at which the null hypothesis of zero correlation is rejected. Coefficients significant at 10% or better (based on 2-tail test) are in boldface.

Table 3b
Simple Correlation Coefficients of Main Control Variables with Firm-specific Stock Return Variation Variables and with Each Other

$\ln({}_{ROA}\sigma_{\varepsilon}^2)$	$\ln({}_{ROA}\sigma_m^2)$	${}_{ROA}\Psi$	*segs*	*H*	*ln*(*K*)	λ	*lev*	*adv*	*r&d*	*r&d*	*R&D spending*
0.204	**0.116**	**0.121**	-0.093	**-0.173**	**-0.219**	0.070	0.104	0.089	0.020	$\ln(\sigma_m^2)$	*absolute systematic stock return variation*
(0.00)	(0.08)	(0.07)	(0.17)	(0.01)	(0.00)	(0.30)	(0.12)	(0.20)	(0.77)		
	0.771	**0.296**	**-0.182**	**-0.348**	0.018	**-0.117**	0.053	0.059	-0.029	$\ln({}_{ROA}\sigma_{\varepsilon}^2)$	*absolute firm-specific fundamentals variation*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.79)	(0.08)	(0.40)	(0.39)	(0.68)		
		-0.378	**-0.291**	**-0.21**	0.061	-0.094	**0.155**	-0.060	-0.059	$\ln({}_{ROA}\sigma_m^2)$	*absolute systematic fundamentals variation*
		(0.00)	(0.00)	(0.00)	(0.36)	(0.17)	(0.00)	(0.38)	(0.39)		
			-0.172	**-0.191**	-0.066	0.022	**-0.121**	**0.174**	0.048	${}_{ROA}\Psi$	*rel. firm-specific fundamentals variation*
			(0.00)	(0.00)	(0.33)	(0.74)	(0.07)	(0.01)	(0.50)		
				-0.080	**0.257**	0.081	**-0.111**	0.095	0.023	*segs*	*corporate diversification*
				(0.25)	(0.00)	(0.24)	(0.10)	(0.16)	(0.73)		
					0.112	**0.044**	0.076	**-0.138**	-0.045	*H*	*Herfindahl index*
					(0.10)	(0.00)	(0.25)	(0.05)	(0.51)		
						-0.359	0.066	0.045	-0.081	*ln*(*K*)	*size*
						(0.00)	(0.32)	(0.51)	(0.24)		
							-0.207	**0.141**	**0.345**	λ	*liquidity*
							(0.00)	(0.00)	(0.00)		
								-0.361	**-0.132**	*lev*	*leverage*
								(0.00)	(0.04)		
									0.111	*adv*	*advertising spending*
									(0.10)		

Note for Table 3b. This table reports correlation coefficients. (seg, H, ln(K), λ, lev, adv, r&d) sample is constructed using 1990-1992 data and consists of 214 three-digit industries based on 6,021 firms. $\ln({}_{ROA}\sigma_{\varepsilon}^2)$, $\ln({}_{ROA}\sigma_m^2)$, and ${}_{ROA}\Psi$ are constructed using 1983-1992 data and consists of 214 three-digit industries based on 5,680 firms. Stock return variation measures ($\ln(\sigma_{\varepsilon}^2)$, $\ln(\sigma_m^2)$, Ψ) are constructed using 1990-1992 data and based on a sample consisting of 214 three-digit industries (6,021 firms). Finance industries (SIC code 6000 - 6999) are omitted. Refer to Table 1 for variable definitions. Correlation coefficients are based on 214 three-digit industries sample. Numbers in parentheses are probability levels at which the null hypothesis of zero correlation is rejected. Coefficients significant at 10% or better (based on 2-tail test) are in boldface.

Table 4
OLS Regressions of Capital Budgeting Quality Variables (Measured as Deviation of Marginal *q* from One) on Firm-specific Stock Return Variation and Control Variables

		4.1	4.2	4.3	4.4	4.5	4.6
dependent variable		*squared deviation of marginal q from 1,* $(\dot{q}-1)^2$			*absolute value of deviation of marginal q from 1,* $\lvert\dot{q}-1\rvert$		
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	**-0.290** (0.03)	**-0.350** (0.02)	**-**	**-0.176** (0.05)	**-0.174** (0.10)	-
absolute systematic stock return variation	$\ln(\sigma_m^2)$	0.146 (0.32)	0.165 (0.27)	-	0.020 (0.74)	0.025 (0.67)	-
relative firm-specific stock return variation	Ψ	-	-	**-0.218** (0.10)	-	-	**-0.138** (0.10)
absolute firm-specific fundamentals variation	$\ln({}_{ROA}\sigma_\varepsilon^2)$	-	**0.220** (0.08)	-	-	0.056 (0.27)	-
absolute systematic fundamentals variation	$\ln({}_{ROA}\sigma_m^2)$	-	-0.099 (0.37)	-	-	-0.020 (0.65)	-
relative firm-specific fundamentals variation	${}_{ROA}\Psi$	-	-	0.122 (0.25)	-	-	0.028 (0.53)
corporate diversification	*segs*	-	-2.679 (0.59)	-1.707 (0.73)	-	-0.742 (0.71)	-0.492 (0.81)
Herfindahl index	*H*	-	0.745 (0.31)	0.897 (0.20)	-	**0.481** (0.10)	**0.515** (0.07)
size	*ln*(*K*)	-	-0.005 (0.93)	0.020 (0.70)	-	0.028 (0.20)	**0.034** (0.10)
liquidity	$\hat{\lambda}$	-	-0.101 (0.59)	-0.079 (0.68)	-	-0.019 (0.81)	-0.013 (0.86)
leverage	*lev*	-	-0.323 (0.14)	-0.332 (0.13)	-	-0.128 (0.15)	-0.130 (0.14)
Advertising spending	*adv*	-	2.266 (0.23)	2.190 (0.25)	-	1.001 (0.20)	0.988 (0.20)
R&D spending	*r&d*	-	**1.630** (0.05)	**1.636** (0.05)	-	0.418 (0.22)	0.421 (0.22)
F-statistics		**14.001** (0.00)	**5.832** (0.00)	**6.230** (0.00)	**19.988** (0.00)	**11.965** (0.00)	**11.805** (0.00)
Regression R^2		0.060	0.117	0.098	0.072	0.121	0.113

Note for Table 4. This table reports OLS regression estimation results. The dependent variables are $(\dot{q}-1)^2$ *(Specifications 4.1-4.3) and* $|\dot{q}-1|$ *(Specifications 4.4-4.6). Regressions 4.1 and 4.4 include absolute firm-specific stock return variation,* $\ln(\sigma_\varepsilon^2)$ *and absolute systematic stock return variation,* $\ln(\sigma_m^2)$ *as independent variables. Regressions 4.2 and 4.5 also include absolute firm-specific fundamentals variation,* $\ln({}_{ROA}\sigma_\varepsilon^2)$*, absolute systematic fundamentals variation,* $\ln({}_{ROA}\sigma_m^2)$*, 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 4.6 include relative firm-specific stock return variation,* Ψ*, relative firm-specific fundamentals variation,* ${}_{ROA}\Psi$*, corporate diversification, segs, Herfindahl index, H, size, ln(K), liquidity,* $\tilde{\lambda}$*, leverage, lev, advertising, adv spending, and R&D spending, r&d as independent variables. All regressions also include one-digit SIC industry fixed effects (coefficients are not reported). Sample is 214 three-digit industries. 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 zero coefficient can be rejected. Coefficients significant at 10% level (based on 2-tail test) are in boldface. Quality of capital budgeting variables* ($(\dot{q}-1)^2$, $|\dot{q}-1|$) *are constructed using 1993-1997 data and based on a sample consisting of 214 three-digit industries (6,375 firms). Firm-specific stock return variation measures* ($\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$*, and* Ψ)*, are constructed using 1990-1992 data and based on a sample consisting of 214 three-digit industries (6,021 firms). (seg, H, ln(K),* $\tilde{\lambda}$*, lev, adv, r&d) sample is constructed using 1990-1992 data and consists of 214 three-digit industries based on 6,021 firms.* $\ln({}_{ROA}\sigma_\varepsilon^2)$, $\ln({}_{ROA}\sigma_m^2)$*, and* ${}_{ROA}\Psi$ *are constructed using 1983-1992 data and consists of 214 three-digit industries based on 5,680 firms. Refer to Table 1 for variable definitions.*

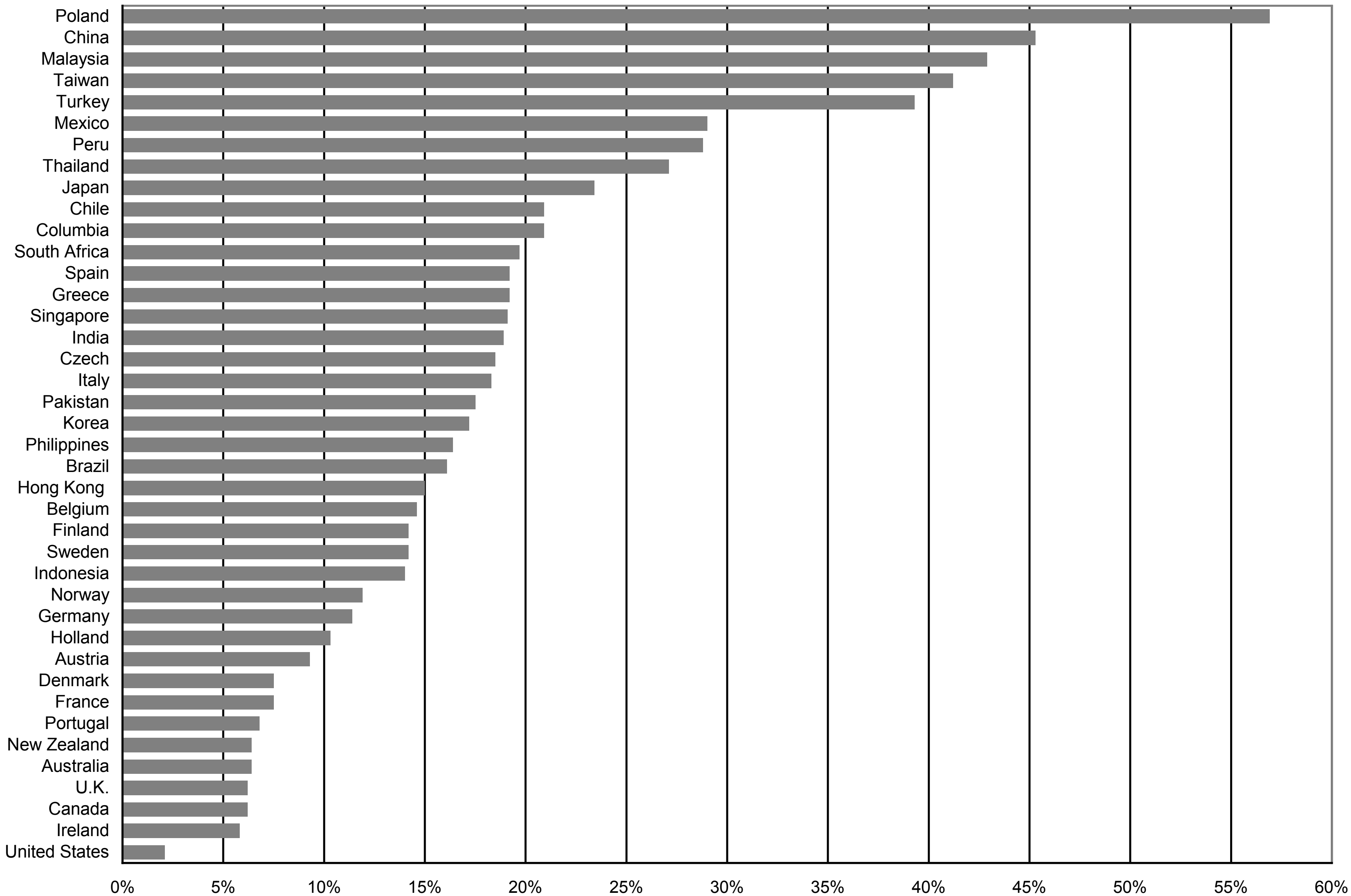
Table 5
Nonlinear LS Regressions of the Capital Budgeting Quality Measures (Measured as Deviation from Threshold Value) on Firm-specific Stock Return Variation and Control Variables

		5.1	*5.2*	*5.3*	*5.4*	*5.5*	*5.6*
dependent variable		*squared deviation of marginal q from an endogenously estimated threshold value h,* $(\dot{q}-h)^2$			*absolute value of deviation of marginal q from an endogenously estimated threshold value h,* $\lvert\dot{q}-h\rvert$		
threshold value of marginal q for capital budgeting	*h*	**0.757** (0.00)	**0.754** (0.00)	**0.753** (0.00)	**0.808** (0.00)	**0.786** (0.00)	**0.719** (0.00)
absolute firm-specific stock return variation	$\ln(\sigma_\varepsilon^2)$	**-0.185** (0.10)	**-0.254** (0.05)	-	**-0.070** (0.05)	**-0.081** (0.05)	-
absolute systematic stock return variation	$\ln(\sigma_m^2)$	0.178 (0.15)	0.195 (0.12)	-	0.016 (0.50)	0.022 (0.40)	-
relative firm-specific stock return variation	Ψ	-	-	**-0.196** (0.08)	-	-	**-0.028** (0.10)
absolute firm-specific fundamentals variation	$\ln({}_{ROA}\sigma_\varepsilon^2)$	-	0.140 (0.19)	-	-	0.051 (0.22)	-
absolute systematic fundamentals variation	$\ln({}_{ROA}\sigma_m^2)$	-	-0.061 (0.51)	-	-	-0.018 (0.68)	-
relative firm-specific fundamentals variation	${}_{ROA}\Psi$	-	-	0.080 (0.38)	-	-	**0.031** (0.10)
corporate diversification	*segs*	-	0.702 (0.87)	1.014 (0.81)	-	-0.721 (0.15)	-0.490 (0.20)
Herfindahl index	*H*	-	**-0.087** (0.06)	**-0.080** (0.08)	-	**0.494** (0.05)	**0.588** (0.01)
size	*ln*(*K*)	-	0.605 (0.33)	0.583 (0.32)	-	**0.023** (0.10)	**0.032** (0.10)
liquidity	λ	-	**-0.295** (0.07)	**-0.292** (0.07)	-	-0.015 (0.81)	-0.010 (0.81)
leverage	*lev*	-	-0.164 (0.37)	-0.162 (0.38)	-	**-0.122** (0.05)	**-0.128** (0.10)
advertising spending	*adv*	-	**3.294** (0.04)	**3.353** (0.04)	-	1.666 (0.30)	1.113 (0.22)
R&D spending	*r&d*	-	**1.870** (0.01)	**1.886** (0.01)	-	0.974 (0.20)	0.968 (0.18)
F-statistics		**12.318** (0.00)	**8.886** (0.00)	**9.837** (0.00)	**17.083** (0.00)	**16.531** (0.00)	**17.210** (0.00)
Regression R^2		0.424	0.479	0.475	0.414	0.480	0.444
F-statistics of Wald test of comparison with specification in Table 4		**735.935** (0.00)	**79.308** (0.00)	**84.141** (0.00)	**404.944** (0.00)	**56.080** (0.00)	**60.734** (0.00)

Note for Table 5. This table reports non-linear LS regression estimation results. The dependent variables are $(\dot{q}$ - h$)^2$ (Specifications 5.1-5.3) and $|\dot{q}$ - h$|$ (Specifications 5.4-5.6) where the threshold level h is estimated endogenously. Regressions 5.1 and 5.4 include absolute firm-specific stock return variation, $\ln(\sigma_\varepsilon^2)$ and absolute systematic stock return variation, $\ln(\sigma_m^2)$ as independent variables. Regressions 5.2 and 5.5 also include absolute firm-specific fundamentals variation, $\ln({}_{ROA}\sigma_\varepsilon^2)$, absolute systematic fundamentals variation, $\ln({}_{ROA}\sigma_m^2)$, 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 5.6 include relative firm-specific stock return variation, Ψ, relative firm-specific fundamentals variation, ${}_{ROA}\Psi$, corporate diversification, segs, Herfindahl index, H, size, ln(K), liquidity, λ, leverage, lev, advertising, adv spending, and R&D spending, r&d as independent variables. All regressions also include one-digit SIC industry fixed effects (coefficients are not reported). Sample is 214 three-digit industries. Finance industries (SIC code 6000 - 6999) are omitted. Numbers in parentheses are probability levels based at which the null hypothesis of zero coefficient can be rejected. Coefficients significant at 10% level (based on 2-tail test) are in boldface. Wald test is computed for each specification in this table where a constraint regression is a corresponding regression in Table 5. Quality of capital budgeting variables $((\dot{q}$ -1$)^2$, $|\dot{q}$ -1$|$) are constructed using 1993-1997 data and based on a sample consisting of 214 three-digit industries (6,375 firms). Firm-specific stock return variation measures ($\ln(\sigma_\varepsilon^2)$, $\ln(\sigma_m^2)$, and Ψ), are constructed using 1990-1992 data and based on a sample consisting of 214 three-digit industries (6,021 firms). (seg, H, ln(K), λ, lev, adv, r&d) sample is constructed using 1990-1992 data and consists of 214 three-digit industries based on 6,021 firms. $\ln({}_{ROA}\sigma_\varepsilon^2)$, $\ln({}_{ROA}\sigma_m^2)$, and ${}_{ROA}\Psi$ are constructed using 1983-1992 data and consists of 214 three-digit industries based on 5,680 firms. Refer to Table 1 for variable definitions.

Figure 1

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



Note for Figure 1. This figure presents Stock Returns Synchronicity in Various Countries as Measured by the Average R^2 of Regressions of Firm Returns on Domestic and US Market Returns. See Yeung, Morck, Yu (2001).

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 Length of Each Bar Is the Group Average Deviation of Marginal *q* from One

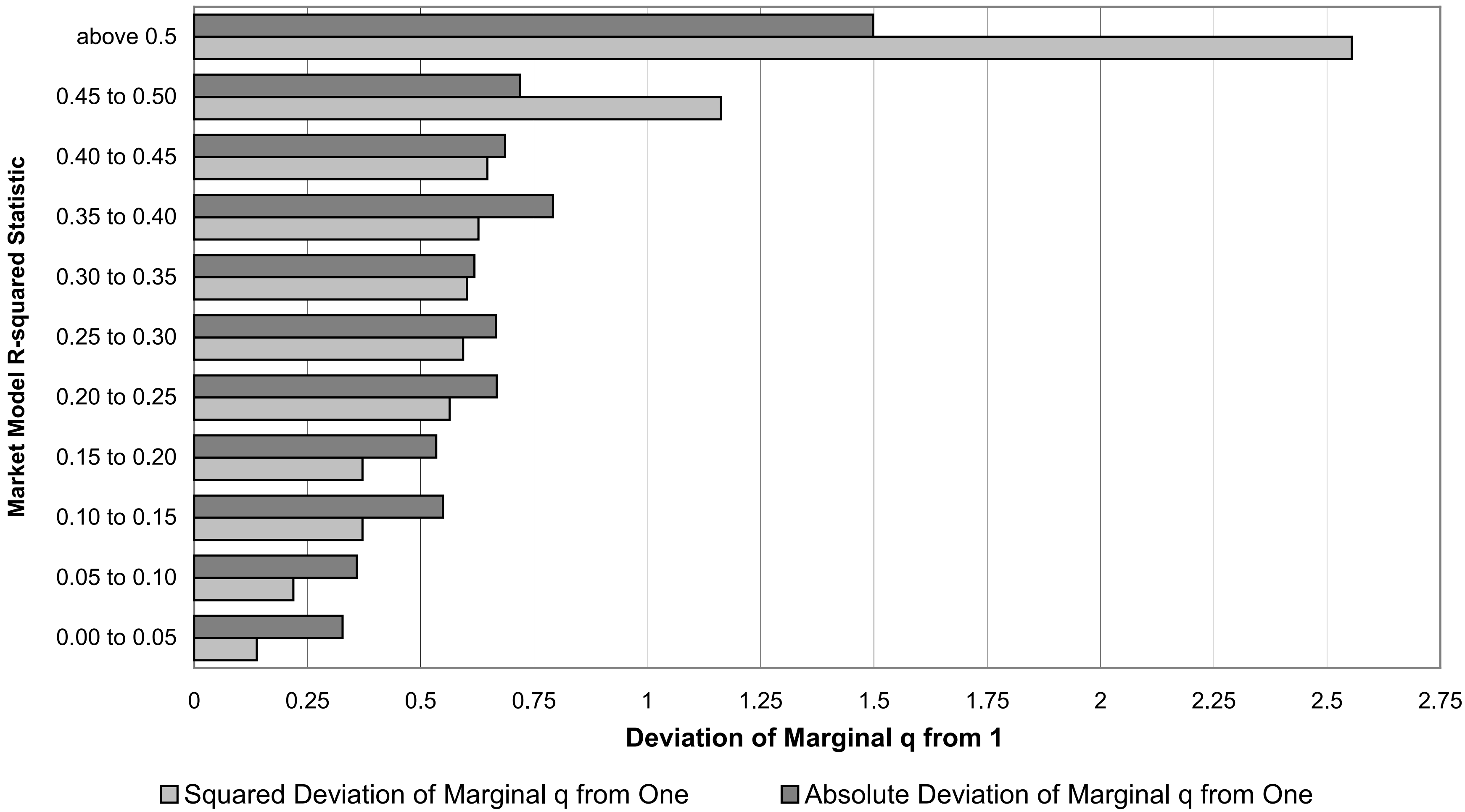


Figure 3

The Proportion of US Industry with Marginal Tobin's q Significantly Greater or Lower Than One at a 10% Confidence Level, with Industries Grouped by Industry-Average Firm-Level Market Model R^2. A low R^2 Indicates a High Firm-specific Return Variation Relative to Market and Industry-related variation. The length of each bar is equal to the proportion of industries whose marginal q is significantly below or above 1 at 10% level