Influence and Inefficiency in the Internal Capital Market: Theory and Evidence

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Abstract: Do influence activities by division managers play a significant role in the investment behavior of multi-divisional firms? Using Compustat Segment data, I find that models of influence activities that lead to signal distortion may have considerable value in predicting capital allocation decisions of multi-divisional firms. Division managers engage in costly influence activities to distort private information about relative investment opportunities and skew capital budgets in their favor. Corporate headquarters may offer ex ante investment contracts that alter the sensitivity of investment to private signals (possibly distorted) and public signals (not distorted, but noisy) relative to first-best.


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Evidence suggests that diversified conglomerates have active internal capital markets--firms use cash flow generated by one division to invest in another.¹ This cross-subsidization is an example of firms making decisions within a hierarchy rather than through the marketplace. The superiority of the hierarchy in the capital allocation process has been attributed to informational advantages not present in the external capital market. Specifically, corporate headquarters has informational advantages relative to external investors and exploits all sources of value by allocating resources to their best use.² Alternatively, headquarters may misallocate funds among divisions because of information distortions that arise from managers pursuing self-interests.³ In this paper, I argue that division managers in multi-divisional firms engage in influence activities and distort information that is transmitted to headquarters thereby skewing capital in favor of their division. I derive the optimal weights placed on different types of signals in headquarters’ capital allocation decisions and evaluate how those weights vary with managerial ability to distort information and the associated private cost to the division manager. Using Compustat Segment data, I find evidence that is consistent with influence activities and signal distortion leading to inefficient capital allocation in multi-divisional firms.

One of corporate headquarters’ primary responsibilities is to allocate capital across divisions to maximize the value of the firm. However, accurate information about relative investment opportunities is typically unavailable. As a part of the capital budgeting process, headquarters relies on several sources of information from division managers—private information or managerial recommendations (that may be distorted) and public information or past profitability of divisions (that cannot be distorted, but is noisy). To the extent that division managers prefer larger capital budgets, they have the incentive to engage in costly influence activities (or rent-seeking behavior) in order to increase the capital allocated to their division. Due to moral hazard problems, I argue that division managers of large, established businesses can distort the transmission of private information about investment prospects in smaller, newer divisions that

1See Lamont (1997) and Shin and Stulz (1997) for evidence of cross-subsidization in diversified firms.
2See Stein (1997), Hubbard and Palia (1998) and Gertner, Scharfstein and Stein (1994) for arguments suggesting that in internal capital markets the residual control rights of senior managers increase monitoring incentives and improve capital allocation relative to the external capital markets.
3 See Rajan, Servaes, and Zingales (1998) (power-seeking model), Scharfstein and Stein (2000) and Scharfstein (1998) (influence cost models) for papers, similar to this one, that focus on information and incentive problems between corporate headquarters and division managers that lead to misallocation of funds among divisions and hence lower firm value.
operate in less predictable businesses. Headquarters cannot observe the large division manager’s action, but does observe the realizations of both signals about small division investment prospects - the possibly distorted, private signal and the noisy, public signal.

An example of the potential effect of influence activities in the internal capital market is IBM’s inability to capitalize on its early success in the development of its personal computer business. Mills and Friesen (1996) argue that

“it was mainframe-myopia that so severely damaged IBM in the 1990’s” and that “division executives began to put the welfare of their own organizations above that of the corporation as a whole... in the resistance of the mainframe division to the introduction of new technology.”

Based on accounts of IBM’s history, it seems that skepticism by the mainframe division (large, established division) about investment opportunities for the IBM PC division (smaller, newer division operating in less predictable business) was partially to blame for the inconsistent success in personal computers.4

One way to address the incentive disparity between headquarters and division managers is to eliminate the internal capital market by either breaking up the firm or instituting policies that limit the role of headquarters in allocating capital.5 Alternatively, two less extreme and potentially more practical approaches are to incorporate investment contracts into the capital budgeting process or to design compensation programs to control influence activities by division managers.6 Incorporating investment contracts into the capital budgeting process is the approach that is modeled in the first half of this paper, while the design of division manager compensation contracts is explored in a related paper (Wulf, 2000). Headquarters designs contracts that specify the optimal weights placed on private and public information in the capital allocation decision (or the sensitivity of division investment to both types of information about investment opportunities).

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4Carroll (1994) documents the power struggles between IBM’s mainframe and personal computer divisions. The manager of the General Products Division “couldn’t finance a personal computer because he had too many projects going”; Frank Cary (chairman) resolved the conflict with the remark “I’ll finance it.” The author argues “as the mainframe profits disappeared, IBM squandered its opportunities to turn the PC or anything else into a business that would wax as mainframes waned.”

5Meyer, Milgrom and Roberts (1992) suggest that divestiture is an organizational solution to influence activities by poor-performing businesses. Another extreme approach is that practiced by Hewlett-Packard in which divisions are required to finance all R&D projects out of funds they generate themselves (Milgrom and Roberts (1992), p. 277).

6Capital budget incentives would specify capital allocation to divisions as a function of the signals about investment opportunities. While not directly observable in practice, firms may offer implicit contracts that accomplish similar goals. For example, Poterba and Summers (1995) find that firms generally use hurdle rates that are higher than the cost of capital and suggest that one reason for this is to address agency problems e.g. managers’ incentive to overstate cash flow projections.
These weights are a function of the ability of managers to distort private information, the private cost of doing so, and the quality of the public information. The optimal contract results in the standard trade-off between the cost of controlling the division manager’s action and the value of that action. In this context, the specific trade-off is between the cost of attaining an accurate private signal and the value of the information the signal provides.

Section II derives the model’s implications by comparing the weight placed on information in second-best contracts to that of first-best. The optimal contract depends on the cost of distorting ex ante investment to align incentives relative to the value of the information the undistorted signal provides. In one case, the value exceeds the cost. Headquarters deters influence activities and signal distortion by placing ‘too little’ weight on the private signal (the one that can be influenced) and ‘too much’ weight’ on the public signal (the one that cannot be influenced) relative to first-best. In the other case, contracts are not designed to mitigate influence activities and, as a result, the private signal may be distorted. This leads to a particular ‘V-shaped’ relationship between the weight placed on the public signal and the manager’s ability to distort information. In both types of contracts, this difference in weight relative to first-best is a measure of investment distortion and it is greater in firms with more influential managers and lower in firms with higher private costs to managers.

Section III preliminarily evaluates evidence of this distortion by estimating investment sensitivity to public signals (or weight placed on public signals) for small divisions across firms. I argue that managers are more capable of distorting information in firms with operations in related businesses and with more divisions. The main empirical finding in this paper is: the weight placed on small division profitability in the investment decision is below first-best and decreasing for firms with diverse businesses and above first-best and increasing for firms with related businesses (i.e. a particular ‘V-shaped’ relationship between investment sensitivity to profitability and the relatedness of firm operations). In a related paper (Wulf, 2000), I find that investment sensitivity to division profitability is lower in firms that link division manager compensation to firm performance (higher private cost to managers) and is higher in firms that operate in industries in which accounting profits are better predictors of investment opportunities (less noisy public signals). In other words, firms appear to place less weight on imperfect accounting profits and more weight on private, distortable signals in allocating capital when compensation incentives for
division managers are aligned via a strong link to firm performance. Finally, the model predicts that multi-divisional firms invest “too much” in small divisions with poor investment opportunities and “too little” in those with favorable investment opportunities. This result, frequently described as “socialism” in the internal capital markets (or strong divisions subsidizing weak ones) is a common result of other models and has general support from the evidence presented in several empirical papers that are described below. These findings suggest that influence activities by division managers play a role in the investment behavior of multi-divisional firms and that certain firms suffer from greater investment distortions.

The main contribution of this paper is to build a model based on managerial efforts to distort information that helps explain how division managers in multi-divisional firms can skew capital budgets in favor of their division. Building on the concept of influence activities, agents can “jam” or distort signals that other’s receive. The model provides a theoretical rationale for inefficient cross-subsidies in internal capital markets and derives the firm’s optimal ex ante incentive contracts to address these inefficiencies. It also makes predictions about the sensitivity of division investment to different sources of information thereby identifying the circumstances under which inefficiencies are more pronounced. For example, the paper’s principal results are that inefficiencies are smaller in firms when division managers are less capable of distorting private information about investment opportunities, when managers face higher private costs of doing so, and when public information is less noisy. The preliminary empirical analysis in this paper, the subsequent analysis presented in Wulf (2000), and various results in the recent literature are generally supportive of the predictions of the theory.

Other recent papers investigate the effect of divisional manager rent-seeking on capital allocation and, as mentioned earlier, generally find support for “socialism” in the internal capital markets. In Rajan, Servaes and Zingales (2000), the principal optimally transfers capital towards the small division with weak opportunities, because this makes this division behave more

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7 This paper can be downloaded from the following website: http://www-management.wharton.upenn.edu/wulfresearch
8 “Influence activities” is a concept developed in Milgrom (1988), Milgrom and Roberts (1990) and Meyer, Milgrom and Roberts (1992) in which lower level managers with private information and vested interests may engage in activities which influence senior manager decisions and result in reduced firm value. Influence activities in this paper take the form of signal-jamming, in which players ‘jam’ or distort signals that others receive [Fudenberg and Tirole (1986) and Holmstrom (1982)]. Specifically, large division managers can take a costly action that affects the distribution of the private signal received by headquarters about small division investment opportunities.
cooperatively in joint production with other divisions. The authors find that the extent of capital misallocation is positively related to the diversity of resources and investment opportunities across divisions. Similarly, I argue that diversity of division size, but also the uncertainty of investment opportunities, determines the degree of information distortion and, in turn, capital misallocation across divisions. However, in this paper, the principal may optimally skew ‘too little’ capital to a stronger small division (in addition to “too much” capital to a weaker one) to offset the desire by large divisions to distort information about the small division. In another related paper, Scharfstein and Stein (2000) develop a two-tiered agency model based on misaligned incentives of the CEO and divisional managers to explain the use of both capital and cash as a means to offset divisional rent-seeking behavior. Providing empirical support for their model, Scharfstein (1998) finds that investment of conglomerate divisions is less sensitive to investment opportunities than stand-alone firms and this pattern is less pronounced in firms where top management owns more equity. Similarly, I estimate the sensitivity of investment of the division to signals about investment opportunities and, using division profitability as one measure, I find that this sensitivity is a function of firm organizational characteristics.

The paper’s approach differs from other papers on internal capital markets by focusing on the relative quality of different information sources in allocating capital across divisions and deriving optimal incentive contracts to offset inefficiencies. In spirit, it is similar to the literature on implicit or relational contracts that explores the combined use of subjective and objective performance measures in incentive contracts to motivate managers and finds that these measures are substitutes.\textsuperscript{9} However, in this setting, instead of informing the principal about unobserved managerial effort, the private and public signals inform headquarters about the unknown investment opportunity.\textsuperscript{10} Consistent with this research and in the vernacular of the incentive literature, headquarters may offer ‘lower-powered’ investment contracts to prevent signal distortion: contracts with a lower weight on the private (or subjective) signal that can be influenced and a higher weight on the public (or objective) signal that cannot be influenced.

\textsuperscript{9} See Baker, Gibbons, Murphy (1994). The investment contract in this paper is an implicit contract that is self-enforcing in the sense that it can be enforced not by the courts but by the firm’s concern for its reputation among managers and ultimately in the labor market (Holmstrom, 1981).

\textsuperscript{10} In addition, similar to Prendergast and Topel (1996), the subjective measures can be distorted by the agents.
The remainder of the paper is organized into five parts. Section I presents the model of influence and signal distortion. Section II solves for the optimal contracts under influence and derives empirical implications for investment behavior. Section III describes the data, outlines the empirical strategy, and presents the results. Section IV discusses the limitations and the robustness of the results. Section V concludes.

I. A Model of Influence and Signal Distortion

Consider a firm with two divisions: a large, established division (L) with known returns; and a smaller, newer division (S) with unknown returns. Headquarters (H) faces a fixed capital budget for new investment and invests in either S or L (or both). H wants to maximize investment returns, while the division managers of S and L prefer larger budgets. The manager of L (hereafter referred to as L) is influential and can engage in costly influence activities to distort private signals that H receives about investment returns in S and thereby skew capital in favor of L. In order to control signal distortion, H offers ex ante investment contracts to division managers that make investment rules contingent on signals about investment opportunities in S and the environment in which the manager operates (characterized by the exogenous parameters).

A. Influence Activities and Signal Distortion

Investment in S generates either low returns (bad type) or high returns (good type). S’s type is represented by \( t \in \{ t_b, t_g \} \). H does not know the type, but knows its distribution: \( \Pr(t_b) = \theta \) and \( \Pr(t_g) = 1 - \theta \) where \( \theta \in (0,1) \). H also observes two signals about S’s type: a public signal (that cannot be influenced by L, but is noisy) and a private signal (that can be influenced). The public signal is denoted by \( \Pi \in \{ \Pi_b, \Pi_g \} \) and is a function of S’s type and some noise. The distribution of \( \Pi \) is defined by the following conditional probabilities: \( \Pr(\Pi_b / t_b) = \Pr(\Pi_g / t_g) = \psi \) and \( \Pr(\Pi_b / t_g) = \Pr(\Pi_g / t_b) = 1 - \psi \), where \( \psi \in (0,1) \) is a parameter representing the quality or ‘fraction right’ of the public signal (and \( 1 - \psi \) represents the noise in the public signal). Thus, given a bad type, the probability that the public signal also will be bad is equal to \( \psi \). An

\[ \text{For simplicity, it is assumed that the small division manager (S) is not influential (i.e. S is a passive agent).} \]
\[ \text{Without loss of generality, and to eliminate duplicate cases, I restrict} \ \psi \ \text{to} \ \psi \in (1/2,1). \]
example of the public signal is division profitability. While S’s profitability is a noisy indicator of investment opportunities, it is not likely to be distorted by L.\(^\text{13}\)

In addition to the public signal, H receives a *private signal* that is initially observed by S. Examples of the private signal include information about new product development, the adoption of a division’s product as a standard, or a pending sale to a large customer. While the signal that S observes is perfect, L can take a costly action (i.e. to engage in influence activities or not) that may distort the *transmission* of this signal to H.\(^\text{14}\) Influence activities are efforts that cast doubt on the potential viability of S’s business. They can occur in a variety of settings ranging from formal meetings to casual comments in the hallways.\(^\text{15}\)\(^\text{16}\) The intent of these activities is unknown to H.

The private signal is denoted by \(\sigma \in \{\sigma_b, \sigma_g\}\) and hereafter represents the (possibly distorted) signal that is received by H. If L chooses *not* to influence, this signal reveals S’s type with certainty (i.e. \(\sigma = t\)). However, if L chooses to influence, the private signal observed by H will be distorted with some probability. Specifically, with probability \(\phi\), H will receive a *bad* private signal when S’s type is *good*.\(^\text{17}\) The conditional probabilities given influence by L are

\[
\Pr_{\phi=\sigma} (t / g) = \phi \quad \text{and} \quad \Pr_{\phi=\sigma} (t / g) = 1 - \phi
\]

where \(\phi \in (0, 1)\) is a parameter representing the ‘distortion

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\(^{13}\) One way in which L could directly distort the profits of S is through transfer pricing. L could charge S high prices for intermediate goods. However, I assume these effects are minimal.

\(^{14}\) The assumption that the private signal observed by S is perfect can be relaxed without affecting the qualitative results.

\(^{15}\) To cite an example to fix ideas, the author used to work for a large financial institution with three primary product segments. In considering the investment associated with a new business opportunity, and as a member of the firm’s investment committee, the Executive Vice President of the large, established division supported investment in the new business if the unit would reside in his division, but was less optimistic about the new business’s prospects if the unit was going to reside in another division. Support from existing managers was critical for the success of new business opportunities in this financial institution. Several opportunities were passed up and subsequently were successfully pursued by smaller firms.

\(^{16}\) In another example, in an investment committee meeting in the early 1980s, the manager of the IBM mainframe division (the large, established division at that time) may have strongly questioned the market projections for personal computers (the small, newer division at that time). It’s possible that questioning by the influential manager may have prevented a proposed investment in a state-of-the-art personal computer plant (even though the investment should have been made).

\(^{17}\) It is assumed that L has no private information about S’s type and either chooses to influence the transmission of S’s private information to H or not (i.e. a moral hazard problem). Alternatively, this could be modeled as an adverse selection problem in which L also has information about S’s type. However, due to the asymmetric effect of influence activities (i.e. only good private signals can be distorted), this change would not affect the qualitative results of the model.
success’ of L’s action on the private signal.\textsuperscript{18} Finally, if L chooses to influence, a private cost is incurred (c).\textsuperscript{19}

H designs ex ante investment contracts with commitment for each division manager (S and L) that specify investment levels and that are functions of both private (\(\sigma\)) and public (\(\Pi\)) signal realizations (and the exogenous parameters--\(\theta, \phi, \psi, c\)), but not of S’s type (t) since it is unobservable to H.\textsuperscript{20} The optimal contracts offered to S and L are represented by \(I^{S}\) and \(I^{L}\), where I is the investment in each division given both signal realizations.

### B. Technology and Preferences

Headquarters represents shareholders and maximizes shareholder wealth defined as the sum of expected returns net of investment in each division. I assume linear returns from investment in both divisions and denote \(r_{i}^{S}\) and \(r_{i}^{L}\) as the respective rates of return net of the cost of investment in S and L. The net return from S is a function of S’s type and is equal to \(r_{i}^{S} \cdot I^{S}(\sigma, \Pi)\), while the net return from L is known and is equal to \(r_{i}^{L} \cdot I^{L}(\sigma, \Pi)\). I assume that \(r_{g}^{S} > r_{b}^{S} > r_{b}^{L}\) and that the expected return from investment in S equals the known return from investment in L (i.e. \(\theta r_{b}^{S} + (1-\theta) r_{g}^{S} = r_{b}^{L}\)).\textsuperscript{21} Thus, H’s payoff is defined as the sum of the expected returns net of investment from each division and is given by

\[
E\{r_{i}^{S} \cdot I^{S}(\sigma, \Pi) + r_{i}^{L} \cdot I^{L}(\sigma, \Pi)\}
\]  

\textsuperscript{18}The conditional probability notation implies that while both the public and private signals are dependent upon the type, the noise in the public signal and the probability of successful distortion associated with the private signal are independent.

\textsuperscript{19}While not done in this paper, the private costs of these activities could be modeled as the loss in L’s leisure time which he spends in influence activities and, much more costly in a dynamic setting, the loss in reputation and possibly promotion opportunities if influence activities are discovered. In a related paper (Wulf, 2000), the private costs to the division manager are proxied by the weight placed on firm performance in determining division manager’s annual bonuses. The stronger the link to firm performance, the greater the cost to the manager from distorting information about investment opportunities.

\textsuperscript{20}H offers the optimal contracts with commitment. While this model is a single-stage game, in a repeated game, H would have no incentive to renegotiate the contracts due to the loss in reputation.

\textsuperscript{21}While this assumption simplifies the algebra in finding the solution, the general form of the solution holds for less restrictive assumptions.
Consistent with annual capital budgeting processes within firms and for simplicity, it is assumed that a fixed amount of capital is raised at the corporate level (represented by \( I \)) and then allocated across divisions.\(^{22}\) While this is an extreme assumption and, in many firms capital is not fixed, most firms face an upward sloping capital supply function. Influence activities would be less of a problem in firms with flexibility in their capital budgets. However, so long as there is an increasing cost of capital and divisions ‘pay’ for capital, L has the incentive to reduce the capital allocated to S. In addition to firms facing capital constraints, I assume that divisions can only receive capital from corporate headquarters and that all capital is invested in the two divisions. These assumptions imply that the sum of the investments in both divisions equals the total capital available to invest, i.e.

\[
I^S(\sigma, \Pi) + I^L(\sigma, \Pi) = \bar{I} \quad \text{where} \quad 0 \leq I^S(\sigma, \Pi), I^L(\sigma, \Pi) \leq \bar{I} \tag{2}
\]

Finally, division managers derive utility only from the size of investment in their division, and for simplicity, L’s utility function is the sum of the linear utility from investment in L and the disutility from the private costs of influence, i.e.

\[
U^L = I^L(\sigma, \Pi) - c \tag{3}
\]

Timing occurs as follows: (1) H offers an investment contract to each division manager \([ I^{S*}(\sigma, \Pi) \) to S and \( I^{L*}(\sigma, \Pi) \) to L]. (2) L chooses whether to engage in influence activities or not, and if so, incurs a private cost \((c)\). (3) Both private \((\sigma)\) and public \((\Pi)\) signals are transmitted to H and observed by all players. (4) H implements the investment contracts and allocates capital \((\bar{I})\) between S and L.

This game is solved in two steps. First, I derive the value-maximizing investment rules under the two possible regimes: one in which H ‘deters influence activities’ (D) and the other in which H

\(^{22}\) Taggart (1987) documents capital rationing in practice. Gitman and Forrester (1977) report that 52\% of survey respondents allocated a fixed annual budget among competing projects and Seapens and Scale (1981) report that virtually all (99.5\%) division managers face some form of capital expenditure limit. Theoretically, the fixed capital budget may arise from asymmetric information in the external capital market. Specifically, Bolton and Scharfstein (1990) argue that investors may terminate a firm’s funding if its performance is poor (capital rationing) to ensure that the firm doesn’t divert resources to itself at the expense of investors. Alternatively, Holmstrom and Ricart i Costa (1986) argue that when investment is informative about managerial talent, capital rationing may be used to offset manager’s incentives to overinvest.
‘allows (or induces) influence activities’ (A). Following this, I consider the optimal regime as a function of the four exogenous parameters: $\phi$ (the distortion parameter or the probability that L’s influence distorts the private signal), $\psi$ (the quality of the public signal), $c$ (L’s private cost of influencing) and $\theta$ (the probability that S is a bad type). Since the comparative statics that are relevant to the empirical part of this paper primarily concern the distortion parameter, I focus on the optimal regime and the implications for investment behavior as a function of $\phi$.\footnote{In Wulf (2000), I derive investment sensitivity to profits as a function of the manager’s private cost and find that...}

\textbf{C. The Firm’s Objective}

In firms with influence activities (i.e. a second-best world), H faces a tradeoff between the cost of attaining an accurate private signal and the value of the information the signal provides. In some firms contracts are designed to deter influence, while in other firms contracts allow or induce influence (i.e. not designed to mitigate influence activities). The type of contract offered by H depends on the values of the exogenous parameters.

In the ‘deter influence regime’ (D), H’s objective is to solve for the investment rule that maximizes the expected sum of the returns net of investment of the two divisions while ensuring that L’s expected utility from influencing is less than or equal to that from not influencing. If $E_D$ ($E_A$) represents the expectations under ‘deter influence’ (‘allow influence’) respectively, the problem is to

\begin{align*}
\max_{I^S, I^L} & \quad V_D = E_D\{r^S_t \cdot I^S(\sigma, \Pi) + r^L \cdot I^L(\sigma, \Pi)\} \\
\text{subject to} & \quad E_A[I^L(\sigma, \Pi)] - c \leq E_D[I^L(\sigma, \Pi)] \\
\text{and} & \quad I^S(\sigma, \Pi) + I^L(\sigma, \Pi) = \tilde{I}
\end{align*}

The incentive compatibility constraint for L [equation (5)] is central to the analysis. The left side is L’s expected utility given L chooses to influence, while the right side is that given a choice of no influence. H makes L indifferent to influencing (i.e. in equilibrium, the incentive compatibility constraint binds) by committing to an ex ante investment contract that reduces...
investment in L and increases investment in S in certain states of the world. In equilibrium, L 
chooses not to influence.24

By contrast, in the ‘allow influence regime’ (A), the objective function takes expectations 
using the probabilities given influence (E_A) and the direction of the inequality in the incentive 
compatibility constraint (5) is reversed. In turn, H offers a contract that, in equilibrium, leads to L 
choosing to influence. 25

II. Optimal Investment Contracts under Influence

A. Investment Rules by Regime

The solutions to the above linear programming problems are presented in Table 1. In this 
table, the pairs represent investment in S and L (I^S, I^L). In order to identify investment 
distortion, the following discussion uses the first-best allocation as a benchmark and compares the 
investment rules under each regime. In a first-best world, H receives an undistorted private signal 
from S and hence knows S’s type. Capital is allocated efficiently between divisions. H allocates 
one to S and all to L when S is bad.26

In a second-best world, some firms design the contract to deter influence, while in other firms 
contracts are designed to allow influence (i.e. not to mitigate influence activities). The optimal 
contract depends on the relative cost of the ex ante distortion of investment for incentive purposes 
compared to the value of the information the undistorted signal provides. First, consider the effect 
of influence activities by comparing the allocation under the deter regime to the first-best 
allocation (case 2.1 versus case 1 in Table 1). The differences occur in the states with incongruent 

24 Substituting in probabilities for the ‘deter influence regime’ and simplifying using equation (2), equations (4) and 
(5) become
V_D = θψ \left[(r_0^S - r^L) \cdot I^S (σ_y, Π_y)\right] + \theta(1−ψ) \cdot [(r_0^S - r^L) \cdot I^S (σ_y, Π_y)] + \theta(1-ψ) \cdot [(r_0^S - r^L) \cdot I^S (σ_y, Π_y)] 
+ (1−θ)ψ \cdot [(r_0^S - r^L) \cdot I^S (σ_y, Π_y)] 
and 
(1−θ)ψ \cdot [(r_0^S - r^L) \cdot I^S (σ_y, Π_y)] + \theta(1−ψ) \cdot I^S (σ_y, Π_y)] + \theta(1-ψ) \cdot I^S (σ_y, Π_y) ≤ c / \phi(1−θ)

25 Substituting in probabilities for the ‘allow influence regime’ and simplifying using equation (2), the firm’s objective 
function becomes
V_A = [θψ \cdot (r_0^S - r^L) + \phi(1-θ)(1−ψ) \cdot (r_0^S - r^L)] \cdot I^S (σ_y, Π_y)] + \theta(1−ψ) \cdot (r_0^S - r^L) + \phi(1-θ) \cdot [ψ(1−θ)] \cdot I^S (σ_y, Π_y)] 
+ (1−θ)(1−ψ)(1−ψ) \cdot I^S (σ_y, Π_y)] + \theta(1-ψ) \cdot I^S (σ_y, Π_y)]

26 At very low levels of the distortion parameter (φ), the manager will not have an incentive to distort signals. The 
expected gains from influence are less than the costs. Firms offer the first-best contract.
private and public signals (hereafter referred to as mixed-signal states). Consider case 2.1i. Note that in the deter regime the private signal is not distorted and $H$ knows $S$’s type. Despite this, $H$ commits to allocate capital to $S$ even when it’s bad. In the first mixed-signal state $(\sigma_b, \Pi_g)$, $H$ allocates ‘too much’ to $S$ ($\Sigma_1$ versus 0) and ‘too little’ to $L$ ($\bar{I} - \Sigma_1$ versus $\bar{I}$) relative to first-best. By penalizing $L$ in the event of a bad private signal, $H$ mitigates the incentive for $L$ to distort the private signal. In equilibrium, $L$ does not influence and $H$ never receives a bad private signal when $S$ is a good type.

Next, compare the two deter cases (case 2.1i versus case 2.1ii). The two cases depend on the distortion-to-cost ratio ($\phi/c$) or the probability that the signal is distorted relative to $L$’s private cost of influence. This ratio can be thought of as a measure of $L$’s ability to influence. Firms with less influential managers (i.e. low distortion-to-cost, $\phi_2$) offer contracts that distort investment in only one mixed-signal state. However, when managers are more influential (i.e. high distortion-to-cost, $\phi_3$), firms offer contracts that require ex ante investment distortion in both mixed-signal states. Specifically, $H$ allocates ‘too much’ to a bad $S$ ($\bar{I}$ versus 0) and ‘too little’ to a good $S$ ($\Sigma_2$ versus $\bar{I}$) relative to first-best. Finally, an important point that is central to the empirical work is that the magnitudes of the investment distortion ($\Sigma_1$ and $\Sigma_2$) increase in the distortion parameter, $\phi$, and decrease in the private cost parameter, $c$.

Some firms design contracts to deter influence activities and the degree of investment distortion depends on managerial ability to distort private signals and the private cost of doing so. However, since deterrence is costly to the firm, it is not always optimal for firms to offer contracts with that as a goal. When the cost of deterrence exceeds the value of the information conveyed through accurate private signals, firms design contracts that allow influence activities (i.e. not to mitigate influence or case 2.2 in Table 1). The allocations in this regime fall into two cases that depend on the distortion-to-noise ratio $[\phi/(1-\psi)]$, which can be thought of as a measure of the relative quality of the two signals. It is important to note that, in the allow regime, bad private signals received by headquarters may be distorted. So, even though the allocations are identical to first-best in one case (case 2.2i -- low distortion-to-noise ratio, $\phi_4$), “too much” capital may be allocated to $L$ ex post when $S$ is good because $H$ acts on a distorted signal. In the other case, since the distortion in the private signal exceeds the noise in the public signal (case 2.2ii --high
distortion-to-noise ratio, $\phi_5$), the good public signal ‘outweighs’ the bad private signal and all capital is allocated to S.

(Insert Table 1 about here.)

B. Distortion in Investment Sensitivity to Public Signals by Regime

Analyses of investment levels are subject to many interpretations. Hence, in order to conduct a more focused evaluation of the use of investment contracts to control influence activities, I analyze investment sensitivity to signals (or optimal weights placed on signals in the investment decision). Specifically, since I have a proxy for the public signal, but not the private signal, I consider investment sensitivity to the public signal for the small division [represented by $S_{\Pi} = \Delta E(I^S | \Pi) / \Delta \Pi$] and evaluate it as a function of the distortion parameter.\(^{27}\) Intuitively, $S_{\Pi}$ represents the change in the capital allocated to S as the public signal changes from bad to good.

In a first-best world, influence activities do not exist and the private signal is undistorted. H offers a contract that does not depend on the probability of signal distortion. Hence, while investment sensitivity to the public signal in the first-best contract ($S_{\Pi_{\text{FB}}}$) is a function of the signal-to-noise ratio of the public signal and the odds ratio of a bad type, it is not a function of the distortion parameter (Figure 1). However, in a second-best world, investment sensitivity to the public signal is a function of $\phi$. In what follows, I derive investment sensitivity (or weight on the public signal) for both deter and allow regimes, and then determine the optimal regime as a function of the parameters.

In the deter regime, investment sensitivity to the public signal ($S_{\Pi_{\text{D}}}$) is greater than first-best and is an increasing function of the probability of distortion (Figure 1). In other words, the increase in the capital allocated to S as the public signal changes from bad to good is higher than

\(^{27}\)I derive expected investment in the small division conditional on the public signal by averaging over the private signal realizations [represented by $E(I^S | \Pi)$]. For example, in the ‘deter regime’, expected investment in S conditional on a bad public signal and investment sensitivity to the public signal are represented by:

$$E(I^S_{\Pi_{b}} | \Pi_{b}) = Pr_{p} (\sigma_{p} / \Pi_{b}) \cdot I^S_{\Pi_{b}} (\sigma_{p}, \Pi_{b}) + Pr_{g} (\sigma_{g} / \Pi_{b}) \cdot I^S_{\Pi_{b}} (\sigma_{g}, \Pi_{b})$$

and $S_{\Pi_{\text{D}}} = \frac{\Delta E(I^S_{\Pi_{d}} | \Pi) / \Delta \Pi}{E(I^S_{\Pi_{d}} | \Pi_{d})} - E(I^S_{\Pi_{b}} | \Pi_{b})$. This derivation is necessary for an explicit mapping to the observables.
first best and this difference is greater in firms with higher probabilities of signal distortion. The reasoning is as follows. In order to deter influence, firms commit to making division investment less sensitive to the private signal (the one that can be influenced) and more sensitive to the public signal (the noisy signal that cannot be influenced). Greater weight is given to the public signal in a way that is ex post inefficient (i.e. $S_{\Pi D} \text{ is 'too high' relative to } S_{\Pi FB}$).\(^{28}\)\(^{29}\) This difference in the weights ($S_{\Pi D} - S_{\Pi FB}$) is one measure of the investment distortion and it is greater in firms with more influential managers (i.e. firms with larger distortion parameters). In the vernacular of the incentive literature, H offers ‘lower-powered’ investment contracts to prevent signal distortion: contracts with a lower weight on the signal that can be influenced and a higher weight on the signal that cannot be influenced relative to first-best.

(Insert Figure 1 about here.)

In contrast, in the allow regime, investment sensitivity to the public signal ($S_{\Pi A}$) is below first-best and is a decreasing function for low probability of distortion ($\phi_4$), and is above first-best and is an increasing function for high probability of distortion ($\phi_5$) (Figure 2). That is, there is a ‘V-shaped’ relationship between investment sensitivity to the public signal and the probability of distortion. The reasoning is as follows. Firms offer contracts that allow influence activities. In this case, the cost of achieving an accurate signal exceeds the value of the additional information. When the public signal is noisy relative to the private signal (low distortion-to-noise ratio, $\phi_4$), H makes investment less sensitive to the public signal and more sensitive to the private signal relative to first-best. Lower weight is given to the public signal in a way that is ex post inefficient (i.e. $S_{\Pi A}$ is ‘too low’ relative to $S_{\Pi FB}$). However, when the public signal is more informative than the private signal (high distortion-to-noise ratio, $\phi_5$), greater weight is given to it relative to

\(^{28}\) Alternatively, ‘too little’ weight is given to the private signal relative to first-best i.e. $S_{\Pi D} < S_{\Pi FB}$. Since I don’t observe the private signal, in the empirical work in the next section, I focus on investment sensitivity to the public signal.

\(^{29}\) This concept and it’s description are analogous to that described in Prendergast and Topel (1996).
first-best. Similar to the deter regime, this inefficiency is greater in firms with higher probabilities of signal distortion.

C. Optimal Investment Contract (or Preferred Regime)

The value-maximizing investment rules (Table 1) determine L’s choice and lead to implications for investment behavior for each regime (Figure 1 and 2). However, these rules say nothing about which regime is optimal for H. By comparing the degree of investment distortion under each regime, I determine the optimal contract (or preferred regime) as a function of the exogenous parameters. As mentioned earlier, since the relevant comparative statics for the empirical part of this paper primarily concern the distortion parameter, I focus on the optimal contract as a function of $\phi$.  

In a first-best world, investment sensitivity to the public signal is not a function of the distortion parameter. In contrast, in firms with influence problems, investment behavior is a function of managerial ability to distort private signals. While the precise solutions vary depending on parameter values, there are two distinct cases for empirical evaluation.

30 The difference in investment behavior below the critical value ($\phi_1$) versus above is caused by the switch of investment levels in the mixed-signal state ($\sigma_g, \Pi_g$) between the two cases in the allow regime. The decreasing range of $S_{\text{IA}} (\phi_4)$ can be explained by the probabilistic relationships between investment levels and public signal realizations. Specifically, as $\phi$ increases, there is a higher probability of an inaccurate private signal in the mixed-signal state ($\sigma_g, \Pi_g$) i.e. higher $\Pr(\sigma_g, \Pi_g | t_j)$. (Or, we see good private signals less often.) Also, in this state, H invests zero in S. Since a good public signal leads to low investment, this implies that the sensitivity of investment to the public signal is decreasing. The opposite holds for $\phi_5$.

31 While neither investment rule in the allow regime is a function of $\phi$ (see Table 1), the probabilities associated with expected investment are.

32 The optimal contract is determined by comparing the absolute value of the difference between the investment sensitivity function for each regime and first-best for all values of the distortion parameter i.e. $\min \{ ||S_{\text{ID}} - S_{\text{IB}}||, ||S_{\text{IA}} - S_{\text{IF}}|| \}, \forall \phi$.

33 Firms with influence problems are defined as those firms in which the distortion parameter is large enough for division managers to have the incentive to engage in influence activities, i.e. $\phi \geq \phi_{\min}$.

34 The two patterns depend on the ordering of the critical values of the distortion parameter and, in turn, can be characterized by restrictions on the manager’s private cost ($c$) relative to the size of the capital budget ($I$). Refer to the footnotes in Figures 3 and 4 for specific parameter restrictions.
Investment Pattern 1 (IP1): Investment sensitivity to the public signal is greater than first-best and is an increasing function of the distortion parameter (Figure 3). When private costs of influence to the manager are high relative to the size of the capital budget ($c/I$), it is less costly for the firm to deter influence (i.e. easier to satisfy incentive compatibility). In this case, the value of the information in an accurate private signal is greater than the cost of attaining it. Firms offer ‘lower-power’ investment contracts and place ‘too much’ weight on the public signal and ‘too little’ weight on the private signal relative to first-best. This ex post inefficiency is greater in firms with more influential managers (i.e. larger distortion parameters).

(Insert Figure 3 about here.)

Investment Pattern 2 (IP2): Investment sensitivity to the public signal is less (greater) than first-best and is a decreasing (increasing) function of the distortion parameter for firms with low (high) distortion parameters. This contract leads to a ‘V-shaped’ relationship between investment sensitivity to the public signal and the distortion parameter (Figure 4). When private costs of influence are low relative to the size of the capital budget ($c/I$), it is more costly for the firm to deter influence. In this case, the cost of attaining an accurate private signal exceeds the value of the information. Firms offer contracts that allow activities and place ‘too little’ (‘too much’) weight on the public signal when it is less (more) noisy relative to the distortion in the private signal.

(Insert Figure 4 about here.)

These results lead to the following empirical implication:

**Empirical Implication:** Multi-divisional firms’ investment sensitivity to public signals ($S_{II}$) in small divisions can be characterized by either (i) a high-valued and increasing function of $\phi$ (Figure 3) or (ii) a low-valued and decreasing function for low values of $\phi$ and a high-valued and
increasing function for high values i.e. a ‘V-shaped’ relationship between investment sensitivity to the public signal and the distortion parameter (Figure 4).

III. The Data and Empirical Strategy

A. Data

The primary data used in this analysis are the Compustat Industry Segment (CIS) data. This database reports segment information for approximately 6500 firms per year. Information includes key financial statistics and SIC codes at the segment level. While the level of aggregation of these data is typically higher than that of the division, capital allocation decisions also are made at the line of business (or segment) level. Hence, I use the segment information to represent the division. In addition, I use Compustat’s Annual File for firm-level information.

The analyses include data for the five-year period from 1989 through 1993 and are based on a sample of multi-segment firms with at least two segments that operate in manufacturing industries (i.e., SIC codes from 2000 to 4000). The model distinguishes between two types of divisions within the firm: (i) large, established divisions with known returns (L) and (ii) smaller, newer divisions with unknown returns (S). However, in order to focus on the extremes, the estimation of the investment equation is based only on the small segments. I use the manufacturing segment with the smallest sales in each year to represent the division with the least influential (or passive) manager and the least predictable returns (smaller, newer division). To determine the relatedness of the firm’s operations, I compare the smallest segment’s business to the largest segment’s business. Hence, I use the manufacturing segment with the largest sales in each year to represent the division with the most influential manager and the most predictable returns (larger, established division).

35 In segment reporting data, managers define what constitutes a distinct business at their firm subject to accounting standards. FASB No. 14 and SEC Regulation S-K require firms to report financial information for segments that represent 10% or more of consolidated sales. This ruling defines an industry segment as “A component of an enterprise engaged in providing a product or service, or a group of related products or services primarily to unaffiliated customers (i.e., customers outside the enterprise) for a profit.”

36 For example, Bausch and Lomb report two segments in Compustat: the larger segment is Healthcare (sic 2834) and the smaller segment is Optics (sic 3851).

37 Investment is defined as capital expenditures net of depreciation (the only measure of investment reported at the segment level). Using capital expenditures as a definition of investment ignores the importance of other investments such as R&D, advertising, etc. Since this problem is more severe in non-manufacturing businesses, I focus only on manufacturing segments.

38 I discuss the reasonableness of these proxies in the limitations and robustness section.
Firms reorganize their segments over time leading to a potential selection problem in creating a panel. In light of this reorganization problem and to ensure that the regression of current investment on lagged profits uses data for the same segment, I include only segments with identical identification numbers for the two periods being compared. Observations have been pooled over the 5-year period (1989-1993). The firms and segments that remain in the multi-segment sample meet the following criteria: firms with at least two segments in manufacturing industries, segments which have the same identification number for the two consecutive years of comparison, and segments for which SIC codes and key financial statistics are available. Table 2 in the appendix provides descriptive statistics of the key financial variables at both the firm and small segment levels for the multi-segment firm sample.

B. Empirical Strategy

The central idea behind this paper’s empirical strategy is based on the premise that the probability of signal distortion varies across firms and, as a result, firms with certain characteristics suffer more from investment distortion due to influence activities. Before detailing the empirical specification and results, I describe proxies for the both the public signal and the probability of signal distortion. I use lagged segment profitability (represented by $\Pi_{S1}$ and defined as operating income/assets for S) as a proxy for the public signal about investment opportunities for two primary reasons: (i) due to persistence in profits, current profits are generally a reasonable predictor of future profits, and (ii) while segment profits are noisy predictors of investment opportunities, they are a measure that arguably cannot be distorted by L. For a measure of segment investment opportunity, much of the finance literature uses the median Tobin’s q of stand-alone firms operating in the segment’s industry. However, both Whited (1999) and

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39Since firm reorganization is common, there is a significant attrition problem when matching segments (i.e. matching segment identification numbers) from year-to-year. Approximately 10% of the segments did not match between 1992 and 1993 and an additional 10% did not match when adding 1991.

40 For the small segment in the multi-segment firm sample, the following variables have been used to calculate financial ratios: net sales, operating profit (loss), depreciation, capital expenditures, identifiable total assets and primary SIC code. From the Compustat Annual File, net sales, operating profit (loss), total assets, and the presence of an S&P bond rating were used to calculate firm variables such as sales growth, profits, and degree of capital constraints.

41 For a discussion of current profits (or cash flow) as a good predictor of future profits refer to Gilchrist and Himmelberg (1998).
Chevalier (2000) find evidence suggesting that using median q’s for the industry is problematic. Importantly, including median q for stand-alone firms in the segment’s industry (3-digit SIC) in the investment equation has no effect on the empirical results.

Proxies for the probability of signal distortion are based on two firm characteristics: the relatedness of division operations and the number of divisions within the firm. First, if the firm is more focused (or less diversified) and the businesses of the small and large divisions are closely related, one could argue that L should be more influential in denigrating S’s investment prospects. It follows that the probability of signal distortion is greater in firms with more closely related businesses. For example, IBM’s CEO might be persuaded by the mainframe division manager’s argument about limited investment prospects in the personal computer business, while General Electric’s CEO would probably not elicit the opinion from the aircraft engine division manager about investment prospects in financial services. Thus, focused firms with divisions that operate in related businesses should suffer from greater investment inefficiencies relative to diversified firms with unrelated operations. Alternatively, if the businesses are more related, headquarters might not be as easily influenced. Ultimately, whether managers are more influential in distorting information in focused or diversified firms is an empirical issue, one that this paper unfortunately cannot provide direct evidence to resolve. To measure the relatedness of division businesses, I compare SIC codes for S (the manufacturing segment with the smallest sales) and L (the manufacturing segment with the largest sales) and designate five degrees of business relatedness. The spectrum of division relatedness ranges from the highly diversified firm where division SIC

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42 The use of industry q’s as a proxy for segment investment opportunities suffers from significant measurement error and does not reflect segment specific opportunities. Whited (1999) explicitly discusses problems using this measure in estimating investment-q equations. Correcting for measurement error, she finds that the evidence in favor of internal capital market inefficiencies disappears. Chevalier (2000) also questions the use of Tobin’s q for the division’s industry and the underlying assumption that the investment opportunities facing conglomerate divisions are identical to those of stand-alone firms in their industries. When I include median q’s for stand-alone firms operating in the segment’s industry (3-digit SIC), the coefficient on segment q is insignificant and the other coefficients remain stable and significant.

43 Other examples that are consistent with managers in related businesses influencing capital allocation decisions are discussed in Christensen (1997). He argues that established firms with a strong customer focus miss important investment opportunities that ultimately are exploited by entrepreneurial firms. For example, Seagate Technology was late in offering a 3.5-inch disk drive primarily because of opposition from the marketing organization and senior executives who argued that customers expressed no need for the product (p. 20). Another explanation is that the managers of the existing 5.25-inch standard opposed the new product and persuaded senior management that the market for the new technology was insignificant.
codes are different at the 1-digit level, to the highly focused firm where the division SIC codes are the same at the 4-digit level.\textsuperscript{45}

The second characteristic used as a proxy for the probability of signal distortion is the number of divisions within the firm. I argue that if the firm has more divisions, the CEO is less knowledgeable about each division’s business and is more likely to be swayed by influential division managers. Or said differently, there is more noise in the transmission of private information in a firm with more divisions. For example, since General Electric’s CEO manages nine business segments (1998), his knowledge of each division and his ability to personally evaluate investment opportunities is more limited relative to a firm with two divisions. It follows that firms with more divisions should suffer from greater investment inefficiencies relative to firms with fewer divisions. The number of divisions within a firm is simply measured by the number of segments, ranging from two to ten. Since the distribution of the number of segments is highly skewed toward fewer segments, I aggregate the data into five categories of number of segments.\textsuperscript{46} In summary, there are five categories of business relatedness and five categories of number of segments used as discrete proxies for the continuous distortion parameter.

Finally, if capital is unlimited at the firm level, division managers don’t compete for a share of a fixed capital budget and the incentive to distort signals should not a problem. However, in general, firms face upward-sloping capital supply functions. I expect firms that have greater capital constraints to suffer more from investment inefficiencies due to signal distortion.\textsuperscript{47} As a measure of the degree of capital constraints, I use the firm’s access to the public debt markets measured by whether the firm has a S&P bond rating. Specifically, firms that have S&P bond ratings are considered less financially constrained, while those that don’t are considered more

\textsuperscript{44} While empirical evidence suggests there are benefits to firms staying close to their core business [e.g. Comment and Jarrell (1995) and Berger and Ofek (1995)], the result in this paper suggests that there are some costs associated with focused firms particularly if similar businesses are managed by separate divisions that compete for resources.

\textsuperscript{45} This is a somewhat crude, but standard approach used to designate increasing levels of relatedness. Other empirical work uses different techniques, some of which try to identify both horizontal and vertical linkages between segments [e.g. Scharfstein (1998)]. Generally, these more refined measures are extremely time-consuming to construct and hence are not feasible for large datasets.

\textsuperscript{46} Evaluating less aggregated categories of firms with more than 5 segments generally leads to insignificant coefficient estimates on those categories due to a limited number of observations in the many segment categories.

\textsuperscript{47} Baxter International announced recently that it would spin off its cardiovascular business to shareholders. “The cardiovascular unit was the area in which Baxter did the fewest acquisitions as the business competed for money with other divisions. Analysts said this was a critical factor hampering growth.” (NY Times; 7/13/99).
financially constrained. Descriptive statistics for the relatedness of businesses, the number of segments, and the degree of capital constraints are presented in Table 3.

C. Empirical Specification and Results

In this section, I specify and estimate an investment equation for small segments to evaluate whether firms in the sample exhibit a pattern of investment sensitivity to profits consistent with that predicted by the influence model. While the ex ante contract is not observable to the econometrician, I do observe ex post investment and profits for the small segment and the relevant firm characteristics. In the econometric specification, I regress investment in the small division ($I_S$) on lagged profits of the small division ($\Pi_{-1}^S$, as the proxy for the public signal), while specifying the regression coefficient ($\beta_0$) as a linear function of firm characteristics ($\Omega$, as proxies for the distortion parameter). I also include other elements of the information set that are informative about the small segment’s investment opportunities. Specifically, I include firm profitability, firm sales growth relative to the industry, and Tobin’s q for the firm as measures of firm (or other segments within the firm) investment opportunities. As mentioned earlier, using Tobin’s q of standalone firms in the segment’s industry is problematic and has no significance on the results. Lastly, I include industry and year fixed effects.

The regression equation that is estimated is the following:

$$I_i^s = \beta_0(\Omega)\Pi_{-1}^S + \beta_1\Pi_{-1}^F + \beta_2X_i^F + \beta_3Q_i^F + \alpha_i + \delta_i + \epsilon_i$$

where

$$\Omega = \gamma_0 + \gamma_1rel + \gamma_2ndiv + \gamma_3cap$$

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48 The issue of whether a firm is capital constrained or not has been extensively discussed in the corporate finance literature. I evaluated several measures of financial constraints including leverage, dividend payout ratios, size of firm defined by sales and assets, and access to public debt markets. I decided to use access to public debt markets measured by whether the firm has a S&P bond rating because it is a simple measure that is the least controversial (and similar to the approach used in Kashyap, Lamont and Stein (1994)). While it is possible to delineate several categories of capital constraints analogous to the two other firm characteristics, this level of refinement is difficult to justify given the current controversy over identifying capital constrained firms.
$I^S_i$ is the $i$th segment’s net capital expenditures (capital expenditures less depreciation) in period $t$ divided by the book value of the $i$th segment’s assets in that period; $\Pi^S_{i,t}$ is the $i$th segment’s operating income in period $t-1$ divided by the book value of the $i$th segment’s assets in that period; $\Pi^F_{i,t-1}$ is identical to the previous variable except calculated for the firm containing the $i$th segment, and $X^F_i$ is the deviation of the firm sales growth in period $t$ from the firm’s industry sales growth in that period (i.e. for the firm containing the $i$th segment); $Q^F_i$ is Tobin’s q for the firm containing the $i$th segment measured as market value of the firm divided by the book value of its assets; $\alpha_i$ is an industry dummy variable for the $i$th segment’s business defined at the 3-digit SIC level, $\delta_t$ is a year dummy variable, and $\epsilon_i$ is an iid disturbance term. The firm characteristics are denoted as $rel$, $ndiv$, and $cap$ and are vectors of dummy variables that represent the degree of relatedness between segment operations, the number of segments within the firm, and the degree of capital constraints, respectively.

The first coefficient in this regression measures the sensitivity of investment to lagged profits for the small division as a function of firm characteristics. Hence, $\hat{\beta}_0(\Omega)$ is an estimate of $S(\phi) = \Delta E(I^S | \Pi) / \Delta \Pi$ as derived in the model (i.e. investment sensitivity to the public signal as a function of the distortion parameter). This coefficient measures how much weight is placed on segment profits in determining segment investment and this weight varies by firm characteristics.

Based on the above specification, I conduct two empirical tests. First, I evaluate whether firm characteristics have any predictive power in determining segment investment sensitivity to profits (i.e. whether the components of $\Omega$ are significant). Second, I test whether the relationship between investment sensitivity to profits and firm characteristics is similar to either the monotonically increasing or ‘V-shaped’ relationship predicted by the model. Specifically, I

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49 Similar to Scharfstein (1998), market value is defined as the book value of assets plus the market value of common equity minus the sum of the book value of common equity and balance sheet deferred taxes.

50 Note, one may argue that the estimate of this coefficient may be biased due to omission of the private signal in the investment equation. However, the theoretical derivation of investment sensitivity to the public signal implies that the investment equation without the private signal is the correct econometric specification. This is because the dependent variable is expected investment and is derived by taking expectations over the private signal. Hence, the effect of the private signal is already incorporated into the dependent variable of the regression equation and including it as an independent variable would result in misspecification.
evaluate whether $\hat{\beta}_0(\Omega)$ is either a high-valued, increasing function of the distortion parameter (Figure 3) or a low-valued, decreasing function for low values of the distortion parameter and a high-valued, increasing function for high values (Figure 4).

The most general model presented in this paper uses five dummy variables to distinguish between degrees of business relatedness and five dummies to identify different numbers of segments. First, let $rel = \{rel0, rel1, rel2, rel3, rel4\}$ denote a vector of dummies such that if the businesses of the small and large manufacturing segments are highly unrelated (i.e. different at the 1-digit SIC level), then $rel0$ equals 1 and the remaining $rel$ dummies (i.e. $rel1$, $rel2$, $rel3$ and $rel4$) equal zero. The same holds true for all other dummies in the vector for higher degrees of business relatedness. Specifically, if the small and large manufacturing segments are highly related (i.e. the same at the 4-digit SIC level), then $rel4$ equals 1 and the remaining $rel$ dummies (i.e. $rel0$, $rel1$, $rel2$ and $rel3$) equal zero.

Next, let $ndiv = \{ndiv2, ndiv3, ndiv4, ndiv5+, ndiv8+\}$ denote a vector of dummies such that if the number of segments in the firm is equal to two, then $ndiv2$ equals 1 and the remaining $ndiv$ dummies equal zero. The other dummies in this vector are similar, except I have grouped some categories due to insufficient data on firms with a large number of segments. Let $rel0$ and $ndiv2$ be the base categories and, as such, they are excluded from the regression. I denote $cap$ as a dummy variable that equals 1 if the firm is more capital constrained (i.e. if it has no S&P bond rating) and zero if it is less capital constrained (i.e. if it has a S&P bond rating). I compare the general model to one that restricts all relatedness coefficients ($rel$) and number of division coefficients ($ndiv$) to be equal to zero. In addition, I report results for both OLS estimation (model 1) and a specification (model 2) that corrects the standard errors for heteroskedasticity across firms and allows for the specification of the correlation structure among observations within firms (Table 4).

The test of whether investment is consistent with the first-best contract is the joint test that all coefficients for each category of firm characteristic are equal to zero. This hypothesis can be rejected at the 1% level of significance, so it’s clear that firm characteristics (business relatedness, number of segments, and degree of capital constraints) are important determinants of investment.

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51 Specifically, $ndiv5+$ represents firms with 5, 6, or 7 segments and $ndiv8+$ represents firms with 8, 9 or 10 segments.
behavior of smaller segments. This finding is consistent with the influence model. If I find that the coefficients are different and the pattern of the differences is consistent with that predicted by the model, then I have additional evidence that supports the effect of influence activities on investment behavior.

In order to test whether the evidence supports either investment pattern (Figure 3 or 4), I compare the changes in investment sensitivity to profits between categories and evaluate whether these differences are significant. In addition, I evaluate the direction of these changes to determine whether investment sensitivity to profits is a decreasing or increasing function of the distortion parameter (proxied by $rel$ and $ndiv$). Specifically, I make successive pairwise comparisons of sensitivity to profits by category of firm characteristic. For example, in model 1 of Table 4, investment sensitivity to profits declines when comparing firms that operate in somewhat related businesses ($-0.0348$ for $rel2$) to more related businesses ($-0.1024$ for $rel3$).

The results in Table 4 suggest that the observed investment behavior is generally consistent with that predicted by Investment Pattern 2: investment sensitivity to the public signal as a function of the probability of signal distortion is ‘V-shaped’ [i.e. it is a low (high)-valued and decreasing (increasing) function for low (high) probabilities of signal distortion]. First, focusing on model 1 (OLS) and the business relatedness variable ($rel$), investment sensitivity increases from $rel0$ to $rel1$, decreases from $rel1$ to $rel2$ to $rel3$, and increases from $rel3$ to $rel4$. Importantly, the differences are significant for three of the four categories (p-values for differences between categories). While a similar pattern holds for the number of segments variable ($ndiv$), the differences are significant in two of the four categories. To improve upon the OLS specification, model 2 (robust) takes into account individual firm effects by correcting the standard errors for heteroskedasticity across firms and allowing for the specification of the correlation structure among observations within firms. In general, the ‘V-shaped’ relationship still holds, however the power of the tests is reduced.

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52One possibility is that the number of segments is important, but that the mapping between $ndiv$ and the distortion parameter may not be linear (as assumed).
53Specifically, in addition to correcting the standard errors for heteroskedasticity, model 2 estimates the correlation matrix within firms placing no constraints on the matrix other than it being symmetric and that the same correlation structure applies to all firms.
54Based on a Hausman test, the random-effects model is not rejected (p-value of .0911). However, since the results are borderline, the fixed effects model is reported in Table 5 in the appendix. While the general pattern still holds, the power of the tests is significantly lower due to the short time span of the panel and the reduced degrees of freedom.
characteristics and the resulting ‘V-shaped’ function from model 2 in Table 4 are illustrated in figure 5.55

Finally, turning to the remaining variables, the negative sign on the capital constrained dummy suggests that capital constrained firms make segment investment less sensitive to public signals. This suggests that the competition for funds is somehow different in financially constrained firms.56 The significance of the coefficients on the firm variables \((\Pi_{-1}^{F}, X^{F}, Q^{F})\) suggests that segment investment is dependent on firm (or other segment) investment opportunities. This is consistent with the finding in other empirical work that firms actively allocate capital across divisions.57

D. Discussion of Empirical Results

The empirical results presented in Table 4 and illustrated in Figure 5 suggest influence activities are an important factor in how headquarters allocates capital to small divisions in multi-divisional firms and that the investment distortions relative to first-best are more pronounced in firms with divisions that operate in related businesses. These results suggest that investment sensitivity to profits varies with firm characteristics in a way that is: (i) inconsistent with first-best investment, and (ii) consistent with the second-best Investment Pattern 2. Specifically, small division investment sensitivity to profitability as a function of firm characteristics is a low-valued and decreasing function for firms with less related businesses and a high-valued and increasing function for firms with more related businesses i.e. a ‘V-shaped’ function. While these results suggest that firms do not design investment contracts explicitly to mitigate influence activities in their internal capital markets, they do suggest that headquarters places weights on signals that are ex post inefficient relative to first-best.58

55The observed investment behavior illustrated in Figure 5 (business relatedness) is consistent with that implied by the optimal contract in Figure 4, except at very high values of the distortion parameter. It may be that high values of the distortion parameter are not observed in the data.
56 The model makes no specific predictions about the effect of capital constraints and this result may be subject to multiple interpretations. However, lower investment sensitivity to profits for constrained firms is in contrast to that found in Fazzari, Hubbard and Petersen (1988) and consistent with that found in Kaplan and Zingales (1997).
57 Related empirical work uses several techniques to evaluate whether capital is actively allocated across divisions. Shin and Stulz (1997) find that small segment investment is a function of other segments’ cash flow. The significance of firm profitability in the above regression is consistent with their finding.
58 The ‘V-shaped’ pattern also suggests that the private costs to managers from influencing are low (i.e. costs of ‘getting caught’ distorting signals are low relative to the potential increase in the division’s capital budget). This is
The preliminary evidence presented in this paper suggests that the cost of deterring influence activities through ex ante investment distortion exceeds the value of the information from undistorted signals. However, this does not necessarily imply that inefficiencies in the internal capital market are insignificant. Firms may use other instruments, e.g. compensation incentives linked to firm performance, to deter influence activities by division managers. In Wulf (2000), I evaluate the design of divisional manager incentive compensation and its effect on capital allocation decisions. I find that multi-divisional firms appear to use these two instruments (compensation incentives linked to firm performance and investment incentives through the capital budgeting process) as substitutes to offset incentives to distort information.\textsuperscript{59} Specifically, I find that as the proportion of incentive pay for segment (or group) managers that is based on firm performance increases, small segment investment is less responsive to segment profitability (and, in turn, I argue that investment is more responsive to managerial recommendations). Moreover, this effect is present in firms with operations in industries in which objective measures (i.e. accounting profits) are less informative about investment opportunities and absent in firms with operations in industries in which accounting profits are more informative.

IV. Limitations and Robustness

One important assumption in the model is the larger, established division manager’s ability to distort private signals about the smaller, newer division’s investment prospects. Empirically, I focus on investment behavior of the smallest manufacturing segment, but use relative division sales size to identify the large, established division. While relative tenure of the division managers might be a better measure of the ability of L to distort information and persuade H, this measure generally is not available. The use of division sales to represent the division manager’s informal power within the organization seems to be a reasonable proxy.\textsuperscript{60} To evaluate this further and consider the extremes, I divide the sample into firms with small segments that account for a lower consistent with the difficulty in holding large division managers accountable for subtle negative comments about other division opportunities that ultimately lead to poor investment decisions.

\textsuperscript{59} This trade-off between the use of capital resources and cash to offset incentives is also considered in Scharfstein and Stein (2000).

\textsuperscript{60} While determining CEO tenure may be possible using proxy statements, determining division manager tenure is significantly more difficult. Usually a division’s size is correlated with the amount of resources controlled by division managers (e.g. size of capital budgets and number of employees) and hence is a reasonable measure of division manager ‘power’ within the firm.
proportion of firm sales (i.e. the ratio of small segment sales to firm sales is below the sample median) and firms with small segments that account for a higher proportion of firm sales (i.e. above the sample median). The evidence further supports the assumption: the ‘V-shaped’ investment pattern is present in the firms in which L should be relatively more influential (i.e. firms with low-share small segments) and absent in firms in which L should be relatively less influential (firms with large-share small segments)(compare columns 2 and 3 in Table 5). In addition to division size, the other proxies that I use as a measure of L’s ability to distort information are business relatedness (measured by SIC codes) and number of segments. While the mapping of these measures to L’s ability to influence are based on anecdotes, and other relationships are possible, these assumptions seem to be reasonable.

Another possible limitation is the assumption that the returns of large divisions are known, or at least, more predictable than the returns of small divisions. Since small divisions do not necessarily operate in developing, less predictable businesses, this asymmetry assumption may not be reasonable. However, two observations suggest that it is. First, to eliminate small divisions operating in declining, more predictable businesses and to focus on those in growing, less predictable businesses, I redefine small, newer divisions as those segments which operate in developing, high-growth industries. The ‘V-shaped’ investment pattern still holds (column 1 in Table 6). Moreover, the small segment variance in profitability and sales growth within firms across time periods is greater than the large segment variance. The latter observation suggests there is more uncertainty in small segment returns than in large segment returns, which is consistent with the asymmetric return assumption.

---

61 That is, in firms with low-share small segments, the coefficients on the business relatedness dummies are significantly different from one another and they exhibit a ‘V-shaped’ pattern.

62 Based on a subjective comparison of large and small segment names for a subset of firms in the sample (1993), on average, SIC codes seem to be a reasonable measure of relatedness. For the interested reader, this comparison (related93) is posted on the following web site: [http://www-management.wharton.upenn.edu/wulfresearch](http://www-management.wharton.upenn.edu/wulfresearch)

63 See the discussion in the empirical strategy section of the text for the anecdotes. One could argue that the relationship between influence ability and business relatedness is the opposite (i.e. L is more capable of distorting information about S if the divisions operate in less related businesses). In this case, the evidence still suggests that influence activities affect investment. However, one would conclude that firms operating in less related businesses suffer more from influence activities (the opposite of this paper’s conclusion, but consistent with the findings of RSZ (2000) that focused firms suffer from less inefficiency in their internal capital markets).

64 Includes select 2-digit SIC codes: 28 (Chemicals and Allied Products), 35 (Industrial and Commercial Machinery and Computer Equipment), 36 (Electronic and Other Electrical Equipment and Components), and 38 (Measuring, Analyzing and Controlling Instruments). Refer to Griliches and Mairesse (1984).
One concern in using lagged profitability of the small segment as a proxy for the public signal is that it’s not a forward-looking measure. The measure of segment investment opportunity used in much of the literature is Tobin’s q of the stand-alone firms operating in the same industry as the segment. However, as mentioned earlier, this proxy suffers from measurement error (footnote 42). The inclusion of industry median q (3-digit SIC) for standalone firms as a proxy for segment q in the regression has a negligible effect on the investment pattern and is not significant (not reported).

In addition, it may be argued that the more related segments are, the more likely are firm (or other segment) profits to be a good proxy for the omitted segment q, and hence this may explain part of the pattern. If this were the case, it follows that as segments in the firm become more related, segment investment should be more responsive to the additional information in firm profits about segment opportunities. However, when I interact firm characteristic dummies with the residuals from a regression of firm profits on segment profits, there is no evidence of this pattern. Moreover, the ‘V-shaped’ pattern of coefficients on segment profits in the regression is generally stable (not reported).

Another limitation is that I treat the organizational structure as exogenous and model influence between two divisions only, yet the sample contains firms that have more than two divisions. It is possible to consider a contract that selects the optimal organizational structure in addition to investment incentive contracts. However, due to this problem’s complexity and even though firms reorganize somewhat frequently, I argue that in the short run, it is more costly for the firm to reorganize than to incur investment distortions from offering second-best investment incentive contracts. It is true that by modeling the influence activities between only two divisions, I ignore potential influence between other divisions. To evaluate whether this simplifying assumption has any effect on the empirical analyses, I do two things. First, I control for investment opportunities of other segments by including both lagged firm profitability and Tobin’s q (for the firm) in the

---

65 Specifically, the mean difference in variance for the sample is .0119 in profitability (significant at 10% level) and .0692 in sales growth (significant at 1% level).

66 The limitation of treating the organization structure as exogenous is related to the evidence presented in Chevalier (2000) that suggests that some of the cross-subsidization results in the finance literature may be attributable to selection bias because divisions of diversified firms are not randomly allocated to their corporate parents. However, a large part of the criticism in the Chevalier paper has to do with the use of Tobin’s q for the division’s industry and the underlying assumption that the investment opportunities facing conglomerate divisions are identical to those of stand-alone firms in their industries. The empirical results in this paper are subject to the former criticism, but not as much to the latter because I primarily focus on segment investment sensitivity to segment profits and find that Tobin’s q of stand-alone firms in the industry has no explanatory power in the regressions.
regression. Second, I find that the ‘V-shaped’ investment pattern generally holds in the OLS regression using the sample of firms with only two divisions (column 2 in Table 6). However, in the fixed effects regression the results are noisy and the pattern is no longer consistent with this shape (column 3 in Table 6).

Finally, since there is persistence in profits over time, and because lagged profits are used as a proxy for the public signal, the investment pattern may be a result of a relationship between persistence in profits and firm characteristics. This is difficult to resolve because in order to estimate first-order autoregressive profit equations as a function of firm characteristics, a panel of at least three years is required. Again, as mentioned earlier, this is problematic due to frequent firm reorganizations of segments.

V. Conclusion

In most organizations, resource allocation decisions are made based on several types of information and the quality of the information typically varies by its source. In this paper, I model the capital allocation decision in multi-divisional firms and how headquarters places less weight on subjective, distortable information (e.g. managerial recommendations) and more weight on objective, but noisy information (e.g. historical accounting profits) to offset incentives for division managers to distort information about investment opportunities. The relative importance of managerial recommendations versus accounting profits in the decision depends on the ability of managers to distort information, the private cost of doing so, and the quality of the accounting measures. By arguing that managerial ability to distort private signals is greater in certain types of firms, the model leads to testable implications for small division investment sensitivity to profits across firm characteristics. Finally, I present some preliminary evidence consistent with influence activities that lead to investment distortions in internal capital markets—i.e. a ‘V-shaped’ relationship between investment sensitivity to profits in small divisions and the firm characteristics representing the ability of managers to distort information. These results suggest that while firms

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67 Refer to Gilchrist and Himmelberg (1995) for a discussion of this problem and techniques to resolve it.
68 The empirical results in Table 4 are generally robust to techniques that address outlier problems. (i) When the variables are winsorized at the 1st and 99th percentile of their distribution, the results are similar. (ii) Outliers are identified by comparing squared residuals versus leverage and evaluated for obvious measurement errors.
do not explicitly design investment contracts to mitigate managerial incentives to engage in influence activities, they appear to allocate capital ex post based on distorted information leading to inefficient allocations across divisions. Importantly, these results do not account for other incentive instruments, such as firm-level compensation incentives for division managers, which have been shown to affect investment behavior in multi-divisional firms (Wulf, 2000).

The importance of influence activities in the allocation of capital across divisions may help explain empirical findings about large firms. For example, diversified conglomerates trade at a discount relative to a portfolio of comparable stand-alone firms.69 In addition, large firms have difficulty in creating a desirable ‘entrepreneurial climate’ and are generally less successful than small firms in developing new products and businesses.70 One caveat is that this paper has not explained why multi-divisional firms should exist if investment inefficiencies are prevalent. It could be that other advantages outweigh the costs of an internal capital market. Clearly, there is more work to be done to understand decisions by multi-divisional firms that determine organizational structure.

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70 Using the US Small Business Administration’s 1982 database on innovation activity, Acs and Audretsch (1988) find that small firms were 43% more innovative than larger firms in manufacturing industries and that small firms exhibited an innovation-per-employee ratio 2.38 times greater than large firms. An example of a large company’s difficulty in creating a new business is American Express’ efforts to develop a health claims processing card. From 1989-1992, American Express heavily invested in product development and ultimately gave up the effort. Since then, Healtheon (founded by Jim Clark, the founder of Netscape) has been successful with similar products (based upon company interviews).
Table 1

First-Best Contract and Value-Maximizing Investment Rules—[Deter (D) and Allow (A) Influence Regimes]

[pairs represent small and large division investment ($I^S$, $I^L$)]

<table>
<thead>
<tr>
<th>Cases</th>
<th>Signal Realizations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$(\sigma_b, \Pi_b)$</td>
</tr>
<tr>
<td>1. First-Best Contract ($I^S_{FB}, I^L_{FB}$) ($\phi_1$)</td>
<td>$(0, \bar{I})$</td>
</tr>
<tr>
<td>2. Second-Best Contracts</td>
<td></td>
</tr>
<tr>
<td>2.1 Deter Influence ($I^S_D, I^L_D$)</td>
<td></td>
</tr>
<tr>
<td>i. Low distortion-to-cost ($\phi_2$)</td>
<td>$(0, \bar{I})$</td>
</tr>
<tr>
<td>ii. High distortion-to-cost ($\phi_3$)</td>
<td>$(0, \bar{I})$</td>
</tr>
<tr>
<td>2.2 Allow Influence ($I^S_A, I^L_A$)</td>
<td></td>
</tr>
<tr>
<td>i. Low distortion-to-noise ($\phi_4$)</td>
<td>$(0, \bar{I})$</td>
</tr>
<tr>
<td>ii. High distortion-to-noise ($\phi_5$)</td>
<td>$(0, \bar{I})$</td>
</tr>
</tbody>
</table>

Note: The table presents the four possible combinations of private and public signal realizations; e.g. $(\sigma_b, \Pi_b)$ represents a bad private signal and a bad public signal. Since the signals are both binary random variables, $(I^S, I^L)$ is a four-tuple. $\Sigma_1 = \bar{I} / \psi - c / (\phi(1-\theta)\psi)$ where $\Sigma_1 < \bar{I}$ and $\Sigma_2 = c / [\phi(1-\theta)(1-\psi)]$ where $\Sigma_2 < \bar{I}$. Note there is a minimum value for $\phi$, below which the manager has no incentive to distort the private signal and the first-best is achieved. Definitions for the critical values of $\phi$ follow: (1) first-best: $0 < \phi < \phi_{min} = c / (1-\theta)\psi\bar{I}$; (2.1) deter: $\phi_{min} < \phi_2 < \phi_D = c / (1-\theta)(1-\psi)\bar{I}$ and $\phi_D < \phi_3 < 1$; and (2.2) allow: $\phi_{min} < \phi_4 < \phi_A = (1-\psi) / \psi$ and $\phi_A < \phi_5 < 1$. 
Critical values of $\phi$: $0 < \phi_1 < \phi_{min} (= c/(1-\theta)\psi\tilde{T})$; $\phi_{min} < \phi_2 < \phi_D (= c/(1-\theta)(1-\psi)\tilde{T})$ and $\phi_D < \phi_3 < 1$.

**First-best:**
\[
S_{FB} = \frac{\Delta E(I^5 | \Pi)}{\Delta \pi} = \left[ \frac{1}{1+y/x} - \frac{1}{1+y/x} \right] \tilde{T} \text{ where } x = \psi/(1-\psi) \text{ (the signal-to-noise ratio for the public signal) and } y = \theta/(1-\theta) \text{ (the probability ratio of bad to good types). An analogous measure for the investment sensitivity to the private signal is } S_c = \frac{\Delta E(I^5 | \sigma)}{\Delta \sigma} \text{ where } S_{cFB} = \tilde{T} \text{ (i.e. in first-best, investment in } S \text{ changes from } 0 \text{ to } \tilde{T} \text{ when the private signal changes from bad to good). Note that } S_{FB} \rightarrow S_{cFB} = \tilde{T} \text{ as } \psi \rightarrow 1 \text{ or } x \rightarrow \infty \text{ (i.e. in first-best, investment sensitivity to the public signal converges to that of the perfect, private signal as noise in the public signal goes to zero).}
\]

**Deter Regime:**
\[
S_{ID} = \frac{\Delta E(I^5 | \Pi)}{\Delta \pi} = S_{FB} + \frac{y}{x} \left[ \frac{\tilde{T}}{1 + x/y} - \frac{1/(1-\theta)}{1 + y/x} \right] \text{ where } \phi = \phi_2 \text{ and } x = \psi/(1-\psi) \text{ (the signal-to-noise ratio for the public signal) and } y = \theta/(1-\theta) \text{ (the probability ratio of bad to good types). Note that } S_{ID} \rightarrow S_{FB} \text{ as } \psi \rightarrow 1 \text{ or } x \rightarrow \infty . \text{ Further, } S_{ID} = \tilde{T} - c/(\phi_2(\theta\psi + (1-\theta)(1-\psi))] \text{ where } \phi = \phi_3 .
\]
Critical values of $\phi$ : $0 < \phi_1 < \phi_{\min}$ $[c / (1-\theta) \psi \bar{\tau}]$; $\phi_{\min} < \phi_4 < \phi_A = (1-\psi) / \psi$ and $\phi_A < \phi_5 < 1$.

**First-best** : see footnote under Figure 1.

**Allow Regime** : $S_{\Pi A} = \frac{\Delta E(I_A^S | \Pi)}{\Delta \Pi} = (1-\phi)S_{FB}$ where $\phi = \phi_A$. Note that $S_{\Pi A} \to \bar{T}$ as $\psi \to 1$ and that $S_{\Pi A} \to S_{FB}$ as $\phi \to 0$.

Also, $S_{\Pi A} = \left[1 - \frac{(1-\phi)}{1+\chi \cdot \gamma}\right] \bar{T}$ where $\phi = \phi_5$ and $\chi = \psi / (1-\psi)$ (the signal-to- signal) and $\gamma = \theta / (1-\theta)$ (the probability ratio of bad to good types). Note that $S_{\Pi A} \to \bar{T}$ as $\psi \to 1$ or $\phi \to 1$. 

Figure 2

Small Division Investment Sensitivity to the Public Signal
Allow Regime ($S_{\Pi A}$) vs. First-best ($S_{FB}$)
Figure 3

Small Division Investment Sensitivity to the Public Signal
Investment Pattern 1 (IP1)—High-valued, Increasing Function

There are two distinct patterns of investment behavior that are relevant for empirical evaluation. The two cases depend on the ordering of the critical values of the distortion parameter and, in turn, can be characterized by restrictions on the manager’s private cost of influence ($c$) relative to the size of the capital budget ($I$), the probability of a bad type ($\theta$), and the quality of the public signal ($\psi$). Restating the definitions of the critical values of $\phi$:

$$
\phi_{\text{min}} = \frac{c}{(1-\theta)\psi} ; \phi_A = \frac{1-\psi}{\psi} ; \phi_D < \frac{c}{(1-\theta)(1-\psi)}
$$

Refer to the footnotes in Figures 1 & 2 for the investment sensitivity expressions.

**Investment Pattern 1:** Investment sensitivity to the public signal in the second-best optimal contract is: (i) identical to first-best for $\phi < \phi_{\text{min}}$ and (ii) greater than first-best and an increasing function of $\phi$ for $\phi \geq \phi_{\text{min}}$. This case holds when $\phi_A < \phi_{\text{min}} < \phi_D$ which is true for higher values of $c$ [i.e. $\frac{c}{I} > (1-\theta)(1-\psi)$]. Given this restriction, investment sensitivity to the public signal is illustrated above in Figure 3.
Small Division Investment Sensitivity to the Public Signal

Investment Pattern 2 (IP2) – ‘V-shaped’ Function

Refer to the footnotes in Figures 1 & 2 for the investment sensitivity expressions.

**Investment Pattern 2:** Investment sensitivity to the public signal in the second-best optimal contract is: (i) identical to first-best for $\phi < \phi_{\text{min}}$ (ii) less than first-best and a decreasing function of $\phi$ for some $\phi \geq \phi_{\text{min}}$ and (iii) greater than first-best and an increasing function of $\phi$ for some $\phi \geq \phi_{\text{min}}$. For empirical purposes, the distinction between this case and the previous one is the investment sensitivity in part (ii) of this case. Moreover, in order for the contract to exhibit investment sensitivity that is less than first-best and a decreasing function of $\phi$, it must be the case that $\phi_{\text{min}} < \phi_A$.

This condition is satisfied by the other two cases of critical value ordering: $\phi_{\text{min}} < \phi_D < \phi_A$ [or lower values of $c$ i.e. $\frac{c}{I} < \frac{(1-\theta)(1-\psi)^2}{\psi}$] and $\phi_{\text{min}} < \phi_A < \phi_D$ [or moderate values of $c$ i.e. $\frac{(1-\theta)(1-\psi)^2}{\psi} < \frac{c}{I} < (1-\theta)(1-\psi)$]. However, an additional condition on costs is required to guarantee the initially downward sloping sensitivity for some $\phi \geq \phi_{\text{min}}$ [i.e. $\frac{c}{I} < \frac{(1-\psi)(1-\theta)(1-\psi)+\theta \psi}{2\psi-1}$]. This is derived from the statement that the investment distortion under the deter regime exceeds that under the allow regime at $\phi_{\text{min}}$ [i.e. $(S_{\text{IP2}}(\phi_{\text{min}}) - S_{\text{IPFB}}) > (S_{\text{IPFB}} - S_{\text{IIA}}(\phi_{\text{min}}))$]. Given these restrictions, investment sensitivity to the public signal is illustrated above in Figure 4.
Table 2

Descriptive Financial Statistics for Multi-segment Sample

<table>
<thead>
<tr>
<th>Sample Characteristics</th>
<th>Multi-segment Firms</th>
<th>Smallest Segments (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Sales ($millions)</td>
<td>526</td>
<td>10670</td>
</tr>
<tr>
<td>Assets ($millions)</td>
<td>395</td>
<td>14233</td>
</tr>
<tr>
<td>Net Invest./Assets (I)</td>
<td>.0049</td>
<td>.0374</td>
</tr>
<tr>
<td>Oper. Inc./Assets (Π₁)</td>
<td>.1330</td>
<td>.1066</td>
</tr>
<tr>
<td>Sales Growth</td>
<td>.0381</td>
<td>.1938</td>
</tr>
<tr>
<td>Tobin’s q</td>
<td>1.22</td>
<td>.9379</td>
</tr>
<tr>
<td>Observations</td>
<td>2500</td>
<td>2500</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>680</td>
<td>680</td>
</tr>
</tbody>
</table>

Note: Descriptive statistics for the sample of observations of multi-segment firms. Included are the small manufacturing segments (SIC codes between 2000 and 4000) during the 1989-93 period. Small segments are defined as the manufacturing segment in the firm with the smallest sales. Net investment is defined as the firm’s or segment’s net capital expenditures in period t divided by the book value of the firm’s or segment’s assets in that period. Operating income/assets is defined as the firm’s or segment’s operating income in period t-1 divided by the book value of the firm’s or segment’s assets in that period. Sales growth is defined as the firm’s or segment’s sales growth in period t. Tobin’s q for the firm is measured as firm market value divided by book value of assets. Similar to Scharfstein (1998), market value is defined as the book value of assets plus the market value of common equity minus the sum of the book value of common equity and balance sheet deferred taxes. Source: Compustat
Table 3

Number of Firm-Year Observations with Different Attributes in Multi-segment Sample (rel vs. ndiv)

<table>
<thead>
<tr>
<th>Number of Segments (ndiv)</th>
<th>Different at 1-digit SIC (rel0)</th>
<th>Same at 1-digit SIC (rel1)</th>
<th>Same at 2-digit SIC (rel2)</th>
<th>Same at 3-digit SIC (rel3)</th>
<th>Same at 4-digit SIC (rel4)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 (ndiv2)</td>
<td>174</td>
<td>475</td>
<td>191</td>
<td>43</td>
<td>105</td>
<td>988</td>
</tr>
<tr>
<td>3 (ndiv3)</td>
<td>144</td>
<td>331</td>
<td>144</td>
<td>51</td>
<td>56</td>
<td>726</td>
</tr>
<tr>
<td>4 (ndiv4)</td>
<td>86</td>
<td>216</td>
<td>97</td>
<td>17</td>
<td>33</td>
<td>449</td>
</tr>
<tr>
<td>5+(ndiv5+)</td>
<td>53</td>
<td>162</td>
<td>73</td>
<td>10</td>
<td>10</td>
<td>308</td>
</tr>
<tr>
<td>8+(ndiv8+)</td>
<td>15</td>
<td>10</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>29</td>
</tr>
<tr>
<td>Total</td>
<td>472</td>
<td>1194</td>
<td>506</td>
<td>123</td>
<td>205</td>
<td>2500</td>
</tr>
</tbody>
</table>

Variable Definitions: rel is defined by five relatedness categories representing increasing levels of relatedness of businesses between small and large manufacturing segments (defined by SIC code) in a multi-segment firm, ndiv is defined by five categories representing increasing numbers of segments (2, 3, 4, 5-7 and 8-10). Evaluating less aggregated categories of firms with more than five segments generally leads to insignificant coefficient estimates in these categories due to the limited number of observations in the many segment categories. The split in the sample for the capital constraint characteristic (cap) is approximately two-thirds more constrained firms (firms without S&P bond ratings) and one-third less constrained firms (firms with S&P bond ratings). Not surprisingly, less constrained firms have more segments than more constrained firms do. For the entire sample, the split between firms that have two segments versus more than two segments is approximately 40% versus 60%. For less constrained firms, the split is 25% versus 75%, and for more constrained firms, the split is approximately 50% versus 50%. However, there is no significant difference in the relatedness characteristic between less constrained and more constrained firms.
Table 4
Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics
Modeled by Investment Equation
Dependent Variable is Small Segment Investment Divided by Book Value of Segment Assets ($I^{S}$)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coeff. (s.e.)</th>
<th>Difference (p-value)</th>
<th>Direction of Change</th>
<th>Coeff. (s.e.)</th>
<th>Difference (p-value)</th>
<th>Direction of Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Pi_{-1}^{S}$ (segment oper. inc./assets)</td>
<td>(0.0534^{**})</td>
<td>(.0205) (0.2202)</td>
<td>(0.0035^{***})</td>
<td>(.0205)</td>
<td>(0.069^{*})</td>
<td>(0.067^{*})</td>
</tr>
<tr>
<td>rel1 (same 1-digit SIC)</td>
<td>(0.0170)</td>
<td>(.0139) (0.0000^{***})</td>
<td>(-0.0000^{***})</td>
<td>(.0140)</td>
<td>(0.071^{*})</td>
<td>(0.067^{*})</td>
</tr>
<tr>
<td>rel2 (same 2-digit SIC)</td>
<td>(-0.0348^{**})</td>
<td>(.0140) (0.0054^{***})</td>
<td>(-0.1125^{*})</td>
<td>(.0267)</td>
<td>(0.109^{*})</td>
<td>(0.108^{*})</td>
</tr>
<tr>
<td>rel3 (same 3-digit SIC)</td>
<td>(-0.1024^{***})</td>
<td>(.0267) (0.0005^{***})</td>
<td>(-0.0011)</td>
<td>(.0144)</td>
<td>(0.0011)</td>
<td>(0.0011)</td>
</tr>
<tr>
<td>rel4 (same 4-digit SIC)</td>
<td>(-0.0151)</td>
<td>(.0144) (0.0005^{***})</td>
<td>(-0.0001)</td>
<td>(.0255)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>ndiv3 (3 segments)</td>
<td>(-0.0299^{***})</td>
<td>(.0103) (0.1266)</td>
<td>(-0.0272^{*})</td>
<td>(.0164)</td>
<td>(0.067^{*})</td>
<td>(0.067^{*})</td>
</tr>
<tr>
<td>ndiv4 (4 segments)</td>
<td>(-0.0142)</td>
<td>(.0120) (0.0675^{**})</td>
<td>(-0.0028)</td>
<td>(.0164)</td>
<td>(0.327^{*})</td>
<td>(0.327^{*})</td>
</tr>
<tr>
<td>ndiv5+ (5,6 or 7 segments)</td>
<td>(-0.0531^{***})</td>
<td>(.0213) (0.5924)</td>
<td>(-0.0321)</td>
<td>(.0315)</td>
<td>(0.498^{*})</td>
<td>(0.498^{*})</td>
</tr>
<tr>
<td>ndiv8+ (8,9 or 10 segments)</td>
<td>(-0.0012)</td>
<td>(.0961) (0.0012)</td>
<td>(-0.0001)</td>
<td>(.0379)</td>
<td>(0.498^{*})</td>
<td>(0.498^{*})</td>
</tr>
<tr>
<td>cap (capital constrained)</td>
<td>(-0.0300^{**})</td>
<td>(.0150) (-0.0271^{*})</td>
<td>(-0.0271^{*})</td>
<td>(.0165)</td>
<td>(0.0011)</td>
<td>(0.0011)</td>
</tr>
<tr>
<td>$\Pi_{-1}^{F}$ (firm oper. inc./assets)</td>
<td>(0.0318^{**})</td>
<td>(.0163) (0.0184)</td>
<td>(0.0076)</td>
<td>(.0320)</td>
<td>(0.0076^{*})</td>
<td>(0.0076^{*})</td>
</tr>
<tr>
<td>$X^{F}$ (relative firm sales growth)</td>
<td>(0.0330^{***})</td>
<td>(.0076) (-0.0261^{*})</td>
<td>(-0.0076^{*})</td>
<td>(.0137)</td>
<td>(0.0017)</td>
<td>(0.0029)</td>
</tr>
<tr>
<td>Tobin’s q</td>
<td>(0.0070^{***})</td>
<td>(.0017) (-0.0076^{**})</td>
<td>(-0.0076^{**})</td>
<td>(.0029)</td>
<td>(0.250)</td>
<td>(0.250)</td>
</tr>
<tr>
<td>Observations</td>
<td>2500</td>
<td>(-) (-) (-)</td>
<td>(-) (-)</td>
<td>(-)</td>
<td>(-) (-)</td>
<td>(-)</td>
</tr>
<tr>
<td>R-sq.</td>
<td>0.2156</td>
<td>(-) (-) (-)</td>
<td>(-) (-)</td>
<td>(-)</td>
<td>(-) (-)</td>
<td>(-)</td>
</tr>
</tbody>
</table>

Observations on smallest segment in a firm in a year resulting in unbalanced panel with 680 firms and 2500 segment-years. Model 2 corrects the standard errors for heteroskedasticity across firms and allows for the specification of the correlation structure among observations within firms. Both models include (i) five relatedness categories (rel) representing increasing levels of relatedness of businesses between small and large segments (measured by SIC code) with rel0 as the base category (ii) five number of segment categories (ndiv) with ndiv2 as the base category and (iii) cap equals 1 if firms have no S&P bond rating (financially constrained) and zero otherwise (unconstrained). Relative firm sales growth is defined as the deviation of the firm’s sales growth from the firm’s industry sales growth (2-digit SIC). Tobin’s q is measured as firm market value divided by book value of assets. Significant differences between investment sensitivity to profits across categories is represented by p-values, which are the result of a test on the equality of coefficients between successive pairs of categories. Direction of change represents whether investment sensitivity is increasing or decreasing from one category to the next as firms exhibit characteristics, which suggest increasing probability of signal distortion. *** (**/*) significant at 1% (5/10%) level.
**Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics**
(proxies for the probability of signal distortion)

Model 2 (Robust)

---

**Note:** Investment sensitivity to profits for each category is calculated by summing the coefficient on the base category (rel0 and ndiv2) and the coefficient on each respective dummy variable in model 2 of Table 4. This is an estimate for $\beta(\Omega)$ which, in turn, is the empirical measure of the theoretical construct $S_{\Pi} = \Delta E(I^5 | \Pi) / \Delta \Pi$. The confidence intervals are constructed using the standard errors associated with the dummy variables. For other definitions, refer to the note under Table 4.
Table 5
Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics
Robustness Tests
Dependent Variable is Small Segment Investment Divided by Book Value of Segment Assets (I^5)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Whole Sample (Fixed Effects)</th>
<th>Small, Small Segment Sample (Robust)</th>
<th>Large, Small Segment Sample (Fixed Effects)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>Difference (s.e.)</td>
<td>Coeff.</td>
</tr>
<tr>
<td>( \Pi_1 ) (segment oper. inc./ assets)</td>
<td>.0094</td>
<td>.0436</td>
<td>.0544</td>
</tr>
<tr>
<td></td>
<td>(.0335)</td>
<td>(.0414)</td>
<td>(.0518)</td>
</tr>
<tr>
<td>( rel_1 ) (same 1-digit SIC)</td>
<td>.0611**</td>
<td>.0090</td>
<td>.0612*</td>
</tr>
<tr>
<td></td>
<td>(.236)</td>
<td>(.236)</td>
<td>(.0414)</td>
</tr>
<tr>
<td>( rel_2 ) (same 2-digit SIC)</td>
<td>-.0029</td>
<td>-.0490</td>
<td>.0635</td>
</tr>
<tr>
<td></td>
<td>(.032)</td>
<td>(.032)</td>
<td>(.0377)</td>
</tr>
<tr>
<td>( rel_3 ) (same 3-digit SIC)</td>
<td>-.0325</td>
<td>-.1934**</td>
<td>.0288</td>
</tr>
<tr>
<td></td>
<td>(.0497)</td>
<td>(.0497)</td>
<td>(.0833)</td>
</tr>
<tr>
<td>( rel_4 ) (same 4-digit SIC)</td>
<td>.0699**</td>
<td>-.0197</td>
<td>.0508</td>
</tr>
<tr>
<td></td>
<td>(.0290)</td>
<td>(.0290)</td>
<td>(.0388)</td>
</tr>
<tr>
<td>( \Pi_1 ) (segment oper. inc./ assets)</td>
<td>.0094</td>
<td>.0436</td>
<td>.0544</td>
</tr>
<tr>
<td></td>
<td>(.0335)</td>
<td>(.0414)</td>
<td>(.0518)</td>
</tr>
<tr>
<td>( ndiv ) (segments)</td>
<td>-.0144</td>
<td>-.0185</td>
<td>.0254</td>
</tr>
<tr>
<td></td>
<td>(.015)</td>
<td>(.015)</td>
<td>(.0209)</td>
</tr>
<tr>
<td>( ndiv ) (segments)</td>
<td>.0231</td>
<td>.0022</td>
<td>-.0663</td>
</tr>
<tr>
<td></td>
<td>(.0193)</td>
<td>(.0193)</td>
<td>(.0251)</td>
</tr>
<tr>
<td>( ndiv ) (segments)</td>
<td>.0394</td>
<td>-.0188</td>
<td>-.1128</td>
</tr>
<tr>
<td></td>
<td>(.0370)</td>
<td>(.0370)</td>
<td>(.0423)</td>
</tr>
<tr>
<td>( ndiv ) (segments)</td>
<td>-.0132</td>
<td>-.0357</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(.1731)</td>
<td>(.1731)</td>
<td>(.0565)</td>
</tr>
<tr>
<td>( cap ) (capital constrained)</td>
<td>-.0240</td>
<td>-.0183</td>
<td>-.0625</td>
</tr>
<tr>
<td></td>
<td>(.0239)</td>
<td>(.0239)</td>
<td>(.0209)</td>
</tr>
<tr>
<td>( \Pi_1 ) (firm oper. inc./ assets)</td>
<td>.0151</td>
<td>.0091</td>
<td>.0633*</td>
</tr>
<tr>
<td></td>
<td>(.0287)</td>
<td>(.0287)</td>
<td>(.0550)</td>
</tr>
<tr>
<td>( X ) (relative firm sales growth)</td>
<td>.0049</td>
<td>.0288</td>
<td>.0340***</td>
</tr>
<tr>
<td></td>
<td>(.0092)</td>
<td>(.0092)</td>
<td>(.0229)</td>
</tr>
<tr>
<td>Tobin’s q</td>
<td>.0055</td>
<td>.0448</td>
<td>.0100**</td>
</tr>
<tr>
<td></td>
<td>(.0036)</td>
<td>(.0036)</td>
<td>(.0045)</td>
</tr>
<tr>
<td>Observations</td>
<td>2500</td>
<td>--</td>
<td>1250</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>680</td>
<td>--</td>
<td>413</td>
</tr>
</tbody>
</table>

Notes: For variable definitions and model specifications, refer to footnote to Table 4. The small (large), small segment sample includes firms in which small segment sales relative to firm sales is less (greater) than the median for the whole sample. Using the small, small segment sample, random effects cannot be rejected (p-value of .5247) thus making the robust model an appropriate specification. The power of the tests in the OLS specification is much higher. Using the large, small segment sample, random effects can be rejected (p-value of .0002) thus making the fixed effects model the appropriate specification. However, even in the OLS specification, differences between coefficients across categories are not significant.
### Table 6
**Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics**

**Robustness Tests**

Dependent Variable is Small Segment Investment Divided by Book Value of Segment Assets ($I_3^S$)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>High-growth Industry Sample (Robust)</th>
<th>Two Segment Firm Sample (OLS)</th>
<th>Two Segment Firm Sample (Fixed Effects)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff. (s.e.)</td>
<td>Difference (p-value)</td>
<td>Coeff. (s.e.)</td>
</tr>
<tr>
<td>$\Pi_{1}^S$ (segment oper. inc./ assets)</td>
<td>.0344 (.0427)</td>
<td>.1388 (.0430)</td>
<td>.0882** (.0726)</td>
</tr>
<tr>
<td>rel1 (same 1-digit SIC)</td>
<td>.0445 (.0301)</td>
<td>.0000*** (.0262)</td>
<td>.0398 (.0444)</td>
</tr>
<tr>
<td>rel2(same 2-digit SIC)</td>
<td>-.0313 (.0304)</td>
<td>.0801* (.0299)</td>
<td>.0985** (.0632)</td>
</tr>
<tr>
<td>rel3 (same 3-digit SIC)</td>
<td>-.1532** (.0776)</td>
<td>.0291** (.0540)</td>
<td>-.2289*** (.1437)</td>
</tr>
<tr>
<td>rel4 (same 4-digit SIC)</td>
<td>.0079 (.0328)</td>
<td>.0259 (.0238)</td>
<td>.0774 (.0453)</td>
</tr>
<tr>
<td>$\Pi_{1}^F$ (firm oper. inc./ assets)</td>
<td>.0089 (.0401)</td>
<td>-.0108 (.0262)</td>
<td>-.0537 (.0465)</td>
</tr>
<tr>
<td>$X^F$ (relative firm sales growth)</td>
<td>.0241 (.0218)</td>
<td>.0553*** (.0119)</td>
<td>.0337** (.0166)</td>
</tr>
<tr>
<td>Tobin’s q</td>
<td>.0077 (.0040)</td>
<td>.0091*** (.0030)</td>
<td>.0091 (.0056)</td>
</tr>
</tbody>
</table>

| Observations | 1176 | 988 | 988 |
| Number of Firms | 359 | 316 | 316 |
| R-sq. | .2452 |

Notes: For variable definitions and model specifications, refer to footnote to Table 4. High-growth industry sample includes those segments that operate in select 2-digit SIC codes: 28 (Chemicals and Allied Products), 35 (Industrial and Commercial Machinery and Computer Equipment), 36 (Electronic and Other Electrical Equipment and Components) and 38 (Measuring, Analyzing and Controlling Instruments). Using this sample, random effects cannot be rejected (p-value of .3594) thus making the robust model an appropriate specification. Two segment firm sample includes those firms with only two segments. Using this sample, random effects can be rejected (p-value of .0002), thus making the fixed effects model an appropriate specification.
References:


