Abstract: Is the investment behavior of multi-divisional firms driven in part by influence activities in the internal capital market? Using Compustat Segment data, I find that models of influence activities may have considerable value in predicting capital allocation decisions of multi-divisional firms. Headquarters decides how much to invest in small divisions based on the investment committee’s recommendation (private signal) and observable characteristics (public signal) of the small division. Using a standard moral hazard model, I show that large, established division managers have an incentive to bias private information about investment opportunities in small divisions and skew capital budgets in their favor. Headquarters can reduce these incentives to engage in costly influence activities, by designing contracts which alter the sensitivity of investment to private and public signals. In evaluating optimal contracts, firms face a trade-off between the value of an accurate signal and the cost of mitigating influence problems. This trade-off and the resulting implications for investment sensitivity to both private and public signals depends on the severity of the firm’s influence problem and the quality of the public signal. Using division profits as a proxy for the public signal, firm attributes as proxies for the severity of the influence problem, and the informativeness of profits in predicting firm value as a proxy for the quality of the public signal, I show that manufacturing firms allocate capital to smaller divisions in a way that suggests that influence problems lead to inefficient capital allocation. Moreover, firms with operations in related or less predictable businesses, flatter organizational structures, and tighter financial constraints appear to be more vulnerable to these problems and, as a result, suffer from greater inefficiencies in their internal capital markets.


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1. Introduction

Evidence suggests that diversified conglomerates engage in cross-subsidization in their internal capital markets--firms use cash flow generated by one division to invest in another.\(^1\) This is an example of firms making decisions within a hierarchy rather than through the marketplace (Coase 1937). Why do firms choose the hierarchy, and does this choice increase or decrease the value of the firm? Some argue that corporate headquarters allocates capital across divisions to take advantage of favorable investment opportunities leading to greater firm value, while others suggest the practice is a response to imperfections in the internal capital market resulting in reduced firm value.\(^2\) This paper argues that the multi-divisional form of organization creates incentives for division managers to influence information about investment opportunities and skew capital budgets in their favor. It focuses on the quality of information that headquarters uses to make investment decisions and division investment sensitivity to that information as the relative quality of private and public signals vary. Using Compustat Segment data, I find evidence suggesting that information problems lead 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. As a part of the capital budgeting process, headquarters relies on investment committee recommendations (private signal) and observable characteristics (public signal) about division investment opportunities. To the extent that division managers prefer larger capital budgets, they have the incentive to engage in costly influence activities to skew capital budgets in their favor. Using a standard moral hazard model, I argue that division managers of large, established businesses can influence or bias the private information received by headquarters about investment prospects in smaller divisions that operate in less predictable businesses.\(^3\) Headquarters cannot observe the large division manager’s action, but does observe the realizations of both signals about small division investment prospects--the noisy public signal and the possibly biased private 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 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 which limit the role of headquarters in allocating capital.5 Alternatively, a less extreme and potentially more practical approach is to incorporate incentive contracts into the capital budgeting process to control influence activities by division managers.6 This is the approach that is modeled in the first half of this paper. Headquarters designs contracts with commitment that specify the sensitivity of investment in the small division to private and 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. Headquarters may deter influence activities by distorting ex ante investment and making it less responsive to the corruptible private signal (i.e. offer ‘lower-powered’ incentive contracts to satisfy incentive compatibility).7 By contrast, headquarters may allow influence activities and ultimately make ex post investment decisions based upon inaccurate private signals.

The second half of the paper derives the model’s investment implications given the data constraints and presents the empirical findings. Section 3 compares the investment implications of optimal contracts in the presence of influence activities to first-best investment (i.e. investment in the absence of influence activities). The first, and most important set of analyses evaluates how investment sensitivity to public signals about small division investment opportunity varies with the model’s two key parameters--the severity of the influence problem and the quality of the public signal. The optimal contract implies particular non-monotonic relationships between investment responsiveness to the public signal for the smaller division and both parameters (while first-best investment implies different relationships). I look for evidence of these relationships by using the following proxies in the analysis of multi-divisional firms: (i) division profits proxy for the public signal about small division investment opportunities, (ii) firm characteristics proxy for the severity of the influence problem (relatedness of division operations, number of divisions within the firm,
whether the firm has access to public debt markets), and (iii) industry characteristics proxy for the public signal quality (informativeness of profits in predicting firm value). The second analysis is closer to existing work, but is less general in terms of information used by headquarters to allocate capital across divisions. It evaluates investment levels given the attractiveness of the investment opportunity and is based on a comparison of investment behavior between small divisions of multi-divisional firms and stand-alone firms. While this approach is similar to that used in other papers, its reliance on investment of stand-alone firms as a proxy for first-best investment is problematic.

In summary, the main empirical results presented in Section 4 are: (i) The importance of division profits (as a proxy for the public signal) in determining small division investment varies across multi-divisional firms in a way that suggests these firms allocate capital partly in response to influence problems and hence suffer from investment distortions relative to first-best. Specifically, as influence problems intensify (proxied by firm characteristics), the importance of profits in the investment decision increases for certain types of firms and decreases for others (i.e. a particular non-monotonic relationship). (ii) Firms with operations in related businesses, flatter organizational hierarchies, and tighter financial constraints appear more vulnerable to these problems and suffer from greater investment distortions in their internal capital markets (iii) As the quality of the public signal varies, investment sensitivity to profits cannot be explained by a simple signal extraction story and, for certain parameters, is consistent with the model’s implications. (iv) Multi-divisional firms are more likely to invest more in small manufacturing divisions with poor investment opportunities (measured by future profits and Tobin’s Q) and less in small divisions with attractive investment opportunities relative to stand-alone firms.

There are a number of recent papers that evaluate capital expenditures in multi-divisional firms. Scharfstein and Stein (1997) suggest that managers in poor performing divisions face lower opportunity costs of rent-seeking which leads to ‘socialism’ in the internal capital market--diversified firms overinvest in poor performers and underinvest in good performers. Consistent with this prediction, Scharfstein (1998) finds that investment sensitivity to Tobin’s Q (for the industry) is higher for stand-alone firms and lower for small segments of diversified firms. Rajan, Servaes and Zingales (1998) argue that individual contributions of division managers are hidden in projects that capitalize on division complementarities. The resulting capital allocation distortions are greatest when divisions have diverse opportunities and resources because diversity leads to
differential power by division managers in bargaining. They find that the extent of capital misallocation and the discount at which diversified firms trade is positively related to the diversity of investment opportunities and resources across divisions. Unlike Scharfstein (1998) and similar to Rajan, Servaes and Zingales (1998), this paper argues that division size and diversity of investment opportunities determine the degree of capital misallocation across divisions. In addition, I find that investment distortions are greater in firms with more divisions, firms facing financial constraints, and firms operating in less predictable businesses. However, unlike Rajan, Servaes and Zingales (1998), I find that in less diversified firms (i.e. when the businesses are more related), the problem is more pronounced. This is due to the assumption that, in firms that operate in related businesses, large division managers are more effective in jamming signals about small divisions.

Unlike the above two papers, this paper focuses primarily on the quality of information that headquarters uses to make investment decisions and division investment sensitivity to that information as the relative quality of private and public signals vary. By arguing that large division manager’s ability to jam private signals is more pronounced in certain types of firms, and that the quality of the public signal is greater in more predictable businesses, the model leads to implications for small division investment sensitivity to profits across both firm and industry characteristics of multi-divisional firms. To date, empirical evaluation of incentive theory is quite limited primarily due to data limitations. I address this problem by deriving an explicit link between the implied investment behavior of capital budgeting incentives and observables in a large cross-section of multi-divisional firms. I find evidence suggesting that influence problems in the internal capital market lead to investment distortions in small divisions of multi-divisional firms.

The remainder of the paper is organized into five parts. Section 2 presents the basic model and solves for the optimal contract. Section 3 derives empirical implications which directly link the model’s predictions to the observables. Section 4 presents the empirical results: (i) comparison of investment sensitivity to public signals among small divisions of multi-divisional firms with different firm and industry characteristics, and (ii) comparison of investment levels between small divisions of multi-divisional firms and standalone firms. Section 5 discusses the limitations and the robustness of the results. Section 6 concludes.
2. The Firm’s Problem and Solution

The two divisions are labeled S (small) and L (large). Headquarters (H) faces a fixed capital budget for new investment and must invest in either S or L. However, the investment returns of S are unknown. Specifically, Division S is a smaller, less established division of unknown type led by a manager with limited tenure within the firm (and, for simplicity, acts as a passive agent). Alternatively, Division L is an established division (the core business of the firm) with known type. Headquarters wants to maximize investment returns, while division managers prefer larger budgets. The manager of L has a long history and established reputation giving him the informal power within the firm to influence the opinion of other members of the organization about investment opportunities in S. That is, he can influence private (or internal) information about S’s type, but it is costly to do so.

Headquarters has a choice between deterring or allowing influence activities by the large division manager. The optimal choice (i.e. the one that maximizes returns from investment) depends on the environment within which the firm operates. This environment is characterized by three attributes: the severity of the influence problem, the quality of the public signal, and the private cost to the division manager from influencing private information. Hence, the situation is a standard moral hazard problem with a few complications. Headquarters (principal) determines the value-maximizing investment rules (analogous to cost-minimizing wage schedules) to induce each action (influencing or not) by the division manager (agent). These rules specify divisional investment (payoff to the agent) as a function of a private and public signal (what the principal observes). Subsequently, headquarters determines whether deterring or allowing influence activities is optimal and offers the contract that results in the preferred action. However, in this model, the optimal contract and preferred action depend upon the firm’s environment (i.e. the three attributes mentioned above).

2.1 Influence Activities and Information Structure

Investment in S generates either low returns (bad type) or high returns (good type). Let $t \in \{t_b, t_g\}$ represent S’s type. Headquarters knows only the distribution of $t$: $\Pr(t_b) = \theta$ (bad)
and $\Pr(t_g) = 1-\theta$ (good). As a solution to the influence problem, Headquarters designs ex ante incentive contracts with commitment which depend upon the realization of two signals about S’s type: an incorruptible, but noisy public signal and a corruptible, private signal.

**Incorruptible, Noisy Public Signal ($\Pi$)**

All agents observe the noisy public signal. Let $\Pi \in \{\Pi_b, \Pi_g\}$ represent this public signal which is a function of S’s type and some noise. $\Pi$ is a random variable fully 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. Thus, given a bad type, the probability that the public signal will also be bad is equal to $\psi$. Without loss of generality, and to eliminate duplicate cases, I restrict $\psi$ to $\psi \in (1/2,1)$.

**Corruptible, Private Signal ($\sigma$)**

In addition to the public signal, H observes a corruptible, private (or internal) signal. Denote $\sigma \in \{\sigma_b, \sigma_g\}$ as this private signal. This signal represents information which is held by employees at lower organizational levels (but unknown to H) which the investment committee collects in order to inform H about whether S is good or bad. However, the distribution of this private signal can be affected by L’s influence activities. Specifically, L decides to either engage in costly influence activities or not, and if so, incurs a private cost ($c$). This costly action can be thought of as L using his informal power within the firm to influence the investment committee’s collective opinion. Influence activities include any efforts that cast doubt on the potential viability of S’s business and can occur in a variety of settings ranging from formal meetings to casual comments in the hallways. These activities cannot be observed by H (or the intent of the activities is unknown to H). For example, in an investment committee meeting, the manager of the IBM mainframe division may question the market projections for personal computers and, in doing so, prevent the proposed investment in a state-of-the-art personal computer plant (even though the investment should be made).
The precision of the private signal ($\sigma$) depends upon L’s action ($a$). If L does not engage in influence activities, the private signal is uncorrupted and it reveals the type with certainty, i.e. $\sigma(a_g) = t$. Alternatively, if L does engage in influence activities, the private signal, $\sigma(a_c)$, will be corrupt with some positive probability and a bad private signal will be observed by H when the type is good. The conditional probabilities given the corrupt action are $\Pr_c(\sigma_g|t_g) = \phi$ and $\Pr_c(\sigma_c|t_g) = 1 - \phi$ where $\phi \in (0,1)$ is a parameter representing the “corruption success” of the agent’s action on the private signal (or the severity of the influence problem). Thus, given a good type and a corrupt action by L, the probability that the private signal will be bad is equal to $\phi$.\textsuperscript{14} This assumes that corruption can only generate a bad private signal from a good type and not vice-versa. This assumption is justifiable because L would never want to generate a good private signal from a bad type and cause H to invest more in S. H cannot observe L’s action (or S’s type), but H knows the prior distributions of the random variables in the model and uses this knowledge to determine the optimal contracts.\textsuperscript{15} H offers these contracts with commitment and cannot renegotiate once the signals are observed.\textsuperscript{16} Ultimately, H makes investment decisions based upon the realizations of the private signal (potentially corrupt) and the public signal (uncorrupted, but noisy).

2.2 Headquarters Payoff and Agent Preferences

Headquarters represents shareholders and maximizes shareholder wealth defined as the sum of expected returns net of investment in each division. H designs ex ante investment incentive contracts for each division manager which are functions of both private and public signal realizations, but not of S’s type since it is unobservable to H. Let the optimal contracts offered to S and L be represented by $K^S(\sigma, \Pi)$ and $K^L(\sigma, \Pi)$, where $K$ is the investment in each division given both signal realizations. Since the signals are both binary random variables, $K^S$ and $K^L$ are four-tuples.

For simplicity, I assume linear returns from investment in both divisions. Let $r^S_t$ and $r^L$ be 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 $r^S_t \cdot K^S(\sigma, \Pi)$ where $t \in \{t_b, t_g\}$ and net return from L is
known and is equal to \( r^L \cdot K^L(\sigma, \Pi) \).\(^{17}\) Thus, H’s payoff defined as the sum of the expected returns net of investment from each division is given by \( \mathbb{E}\{r^S_t \cdot K^S(\sigma, \Pi) + r^L \cdot K^L(\sigma, \Pi)\} \).

Since the incentive to corrupt wouldn’t exist if firms had access to unlimited capital, it is assumed that capital for new investment is constrained at the corporate level and that level is represented by \( \bar{K} \).\(^{18}\) In addition, it is assumed that divisions can only receive capital from corporate headquarters and that all corporate capital is invested in the two divisions.\(^{19}\) These assumptions imply that the sum of the investments in both divisions equals the total capital available to invest, i.e. \( K^S(\sigma, \Pi) + K^L(\sigma, \Pi) = \bar{K}, \forall (\sigma, \Pi) \).

Similar to Harris and Raviv (1997), it is assumed that division managers derive utility only from the size of investment in their division. They argue this is justified because managerial compensation schemes cannot fully solve the incentive/information problems inherent in this type of model.\(^{20}\) Also, to ensure that L’s participation constraint is not binding, I assume that the manager’s utility from managing the division exceeds his opportunity cost. 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. \( U^L = K^L(\sigma, \Pi) - C(a) \).

2.3 Players’ Actions: Timing and Consequences

The players’ actions, the timing and consequences are summarized in Diagram 1 below. Headquarters offers an investment rule that either deters influence activities (left branch) or allows influence activities (right branch).
Diagram 1

Players’ Actions: Timing and Consequences

H offers ex ante contract to S and L

Two types of investment rule

Contract deters corruption by L-- Uncorrupted Investment Rule
\( (K_T^S, K_T^L) \)

Contract allows corruption by L-- Corrupt Investment Rule
\( (K_C^S, K_C^L) \)

L’s induced action

L does not corrupt \( (a_C) \)

L does corrupt \( (a_C) \) and incurs cost, c

Probability=\( \phi \)

Probability=1-\( \phi \)

Effect of L’s action on private signal about S

No corruption-- private signal reveals type \( (\sigma = t) \)

Successful corruption-- Inaccurate private signal \( (\sigma \neq t) \)

Unsuccessful corruption-- Private signal reveals type \( (\sigma = t) \)

H implements contract and invests in S and L

Ex ante investment distortion--underinvest in good S overinvest in bad S

Ex post investment distortion--invest based on inaccurate private signal

Ex post investment distortion

Contract deters influence
(Incentive compatible)

Contract allows influence
(Non-incentive compatible)

Nash equilibria in pure strategies are considered. Candidate equilibria for this game consist of a set of strategies for H and L: (i) an offering of an incentive contract to division managers made by H at the beginning of the period which either deters or allows influence activities by L (ii) a choice by L whether to engage in influence activities or not given the contract offered by H.
This game is solved recursively in two steps which is standard in a moral hazard model. First, I solve for the value-maximizing investment rule for each action (represented in the two branches of Diagram 1 and outlined in Section 2.4). Let the value-maximizing investment rule for the uncorrupted action (deter influence) and corrupt action (allow influence) be denoted by \( \{ K_u^S(\sigma, \Pi), K_u^L(\sigma, \Pi) \} \) and \( \{ K_c^S(\sigma, \Pi), K_c^L(\sigma, \Pi) \} \), respectively. The optimal contract (or the preferred investment rule or action) is determined by a comparison of the value functions for each investment rule. However, these value functions are functions of the three parameters which characterize the firm’s environment: \( \phi \) (the “corruption success” parameter or the severity of the influence problem), \( \psi \) (the quality of the public signal), and \( c \) (the agent’s private cost of influencing). Since the comparative statics primarily concern the corruption parameter (or the severity of the influence problem), I evaluate and compare value functions from each investment rule for all values of \( \phi \).

Let the optimal contract (or the contract which induces the action that creates more value for H) be denoted by \( \{ K^S^*(\sigma, \Pi), K^L^*(\sigma, \Pi) \} \).

2.4 Value-Maximizing Investment Rules for Uncorrupted (deter) and Corrupt (allow) Actions

In the absence of influence activities, the private signal reveals S’s type with certainty. Hence, the first-best contract invests: (i) nothing in S and all in L given a bad private signal about S and (ii) all in S and nothing in L given a good private signal. Since the public signal is noisy, the contract depends only on the perfect private signal and not upon the public signal. Since H knows the relative attractiveness of the investment options, capital is allocated efficiently in firms with no influence problem.

However, in the presence of influence activities, capital allocation across divisions will be inefficient relative to first-best. In order to deter influence activities (left branch in Diagram 1), headquarters uses an investment rule which shifts capital between divisions to make L indifferent to each action, but this leads to investment distortion. Since L chooses not to corrupt, the private signal reveals S’s type with certainty. By committing to overinvestment in S when it is known to be bad, H reduces the investment in L and makes L indifferent to engaging in influence activities. Distortion in the investment rule is necessary to satisfy incentive compatibility and thereby deter influence activities and ensure an accurate private signal.
In contrast, when influence activities are *allowed* (right branch in Diagram 1), inefficiencies arise because investment decisions are possibly made based upon corrupt private information. In this case, a good private signal reveals the type with certainty. However, since corruption can generate a bad private signal given a good type, bad private signals may be inaccurate and H may overinvest in S when bad and underinvest in S when good. Thus, in the investment rule which allows corruption, distortions occur because of corrupt private signals. This is in contrast to the investment rule which deters corruption, in which inefficiencies arise from distorting ex ante contracts to satisfy the incentive compatibility constraint.

As mentioned above, to solve for the *optimal* contract, first I solve for the value-maximizing investment rules for each action (i.e. the uncorrupted and corrupt actions—-the left branch and right branch of Diagram 1, respectively). Headquarters’ problem and solution for each action are outlined below.

**Uncorrupted Action (deter influence activities)**

To induce the uncorrupted action or deter influence activities (left branch in Diagram 1), headquarters’ problem is then to follow the investment rule given signal realizations \( K^S(\sigma, \Pi) \) and \( K^L(\sigma, \Pi) \) that maximizes the expected sum of the returns net of investment of the two divisions and ensures that L’s expected gain from the uncorrupted action exceeds that from the corrupt action. Let \( E_u \) represent the expectations using the probabilities given the uncorrupted action and \( E_c \) given the corrupt action.

\[
\begin{align*}
\max_{K^S, K^L} & \quad E_u \{ r^S \cdot K^S(\sigma, \Pi) + r^L \cdot K^L(\sigma, \Pi) \} \\
\text{subject to} & \quad E_c[K^L(\sigma, \Pi)] - c \leq E_u[K^L(\sigma, \Pi)] \\
& \quad K^S(\sigma, \Pi) + K^L(\sigma, \Pi) = \bar{K}, \quad \forall \sigma, \Pi \\
& \quad 0 \leq K^S(\sigma, \Pi) \leq \bar{K}, \quad 0 \leq K^L(\sigma, \Pi) \leq \bar{K} \\
& \quad \forall \sigma, \Pi
\end{align*}
\]

The objective function (1), is the expected sum of the returns net of investment of the two divisions. The constraint in (2) is the incentive compatibility constraint for L. The left side is L’s expected utility given a choice of the corrupt action. The right side is his expected utility given no
corruption. The constraints in (3) state that capital is constrained and that all available capital is invested in the two divisions. The constraints in (4) simply guarantee that the capital allocations are nonnegative and less than total capital available.

As the solution in Table 1 indicates (below), the value-maximizing investment rule to induce the uncorrupted action and deter influence activities, H distorts the ex-ante investment rule in mixed-signal states to satisfy incentive compatibility. Even though H knows S’s type with certainty (the private signal reveals it when L doesn’t corrupt), distortion occurs. Distortion in the investment rule is necessary to satisfy incentive compatibility and thereby deter influence activities and ensure an accurate private signal.

**Corrupt Action (allow influence activities)**

To induce the corrupt action or allow influence activities (right branch in Diagram 1), headquarters’ problem is similar to the previous case except the incentive compatibility constraint now allows L to choose the corrupt action. In the uncorrupted case, this incentive constraint binds, while in the corrupt case it does not. Hence, this problem is a standard inference problem in which headquarters updates the prior distribution of types based upon signal realizations. The objective function takes expectations using the probabilities given corruption, which replaces $E_u$ in (1) with $E_c$. The incentive compatibility constraint induces the corrupt action by changing the direction of the inequality in (2). The capital constraints and the non-negativity constraints remain the same as (3) and (4) respectively.

As the solution in Table 1 indicates (below), the value-maximizing investment rule to induce the corrupt action and allow influence activities depends upon the relative quality of the public signal to the private signal. Unlike the previous strategy (i.e. deter influence activities), when allowing influence activities the investment inefficiencies arise from decisions made using inaccurate private signals. While capital is allocated efficiently in the two good private signal states, in the two bad private signal states, there is a probability of inefficient investment due to decisions based upon inaccurate private signals. Specifically, in the low quality public signal case, there is the probability of underinvestment in S when good. Hence, in the corrupt investment rule, inefficiencies arise due to decisions based upon corrupt information. In contrast and as mentioned above, in the
uncorrupted investment rule, inefficiencies arise from distorting ex ante investment rules to satisfy incentive compatibility.

Table 1

<table>
<thead>
<tr>
<th>Cases</th>
<th>Signal Realizations</th>
</tr>
</thead>
<tbody>
<tr>
<td>(based on parameters--φ,ψ,γ c)</td>
<td>(σb,Πb)</td>
</tr>
</tbody>
</table>

1. Influence is not a problem

1.1 First-Best Contract

(0, K) | (0, K) | (K,0) | (K,0) |

2. Influence is a problem

2.1 Uncorrupted Action (KuS, KuL)

i. Low private cost (γ)

(0, K) | (K,0) | (Δ1, K − Δ1)1 | (K,0) |

ii. High private cost (γ)

(0, K) | (Δ2, K − Δ2)2 | (K,0) | (K,0) |

2.2 Corrupt Action (KcS, KcL)

i. Low quality public signal (ψ)

(0, K) | (0, K) | (K,0) | (K,0) |

ii. High quality public signal (ψ)

(0, K) | (K,0) | (K,0) | (K,0) |

Note: The table presents the four possible combinations of private and public signal realizations; e.g. (σb,Πb) represents a bad private signal and a bad public signal. 1 Δ1 = γ / [φ(1−θ)(1−ψ)] and 2 Δ2 = K / ψ − c / [φ(1−θ)ψ]
2.5 Optimal Contracts (Second-Best) as a Function of the Severity of the Influence Problem

Table 1 specifies the value-maximizing investment rules that induce either the uncorrupted or corrupt action by L. However, these rules say nothing about which action is optimal for different values of the corruption parameter, $\phi$. By evaluating and comparing value functions for each action, I determine the optimal contract (or preferred action) as a function of the corruption parameter (outlined in sections 2 and 3 of the technical appendix that is under separate cover). Depending upon parameter values, several optimal contracts are possible. However, for empirical analysis, the contracts can be grouped into two categories which imply different investment behavior (summarized in Table 2).

Table 2
Optimal Contracts as a Function of Severity of Influence Problem*

<table>
<thead>
<tr>
<th>Severity of Influence Problem ($\phi$)</th>
<th>Low</th>
<th>Moderate</th>
<th>Severe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal Contract 1 (OC1)</td>
<td>Deter</td>
<td>Corruption</td>
<td></td>
</tr>
<tr>
<td>Optimal Contract 2 (OC2)</td>
<td>Deter</td>
<td>Allow</td>
<td>Deter</td>
</tr>
<tr>
<td></td>
<td>Corruption</td>
<td>Corruption</td>
<td>Corruption</td>
</tr>
</tbody>
</table>

* Optimal Contract 1 is more likely to occur in firms facing high private costs and low quality public signals; while Optimal Contract 2 is more likely to occur in firms facing low private costs and high quality public signals.

Optimal Contract 1 (OC1): Headquarters deters influence activities no matter how severe the influence problem by offering an incentive contract which satisfies the incentive compatibility constraint and induces the uncorrupted action. That is, the investment rule for the uncorrupted action is optimal for all values of the corruption parameter. This case is more likely to occur in
firms facing high private costs and low quality public signals. If the private costs to the L are high, it is less costly for H to deter corruption (i.e. easier to satisfy incentive compatibility). And, if the public signal quality is low, H gains more from an accurate private signal and hence deters corruption.

**Optimal Contract 2 (OC2):** Headquarters *allows* influence activities if the firm suffers from moderate influence problems and *deters* influence activities for the extremes (weak or severe influence problems). That is, the investment rule for the corrupt action is optimal for some parameter values (mid-range values of the corruption parameter), while the rule for the uncorrupted action is optimal for both low and high values of the corruption parameter. This mixed case is more likely to occur in firms facing low private costs and high quality public signals. If the private costs to L are low, it is more costly for H to deter corruption (i.e. harder to satisfy incentive compatibility). And, if the public signal quality is high, H gains less from an accurate private signal and hence allows corruption. In summary, firms facing moderate influence problems allow influence activities (i.e. investment rules do not satisfy incentive compatibility) and may make decisions based upon inaccurate signals. However, the information gain from a perfect private signal does not offset the incentive costs of attaining it. For weak influence problems, H deters influence activities because the costs of satisfying incentive compatibility are low. Moreover, for severe influence problems, H deters influence activities because the costs of receiving a corrupt private signal are high.

In the presence of influence activities, both optimal contracts lead to inefficient investment relative to first-best. The specific empirical implications are derived in the next section (Section 3). In general, firms underinvest in small divisions with good investment opportunities and overinvest in those with poor opportunities relative to first-best. In addition, investment responsiveness to private and public signals varies across firms depending upon the severity of the influence problem and the relative quality of private and public signals.

**3. Empirical Implications**

There are two sets of empirical implications outlined in this section. The first set of implications specifies *investment sensitivity to public signals* (proxied by lagged division profits)
about investment opportunities as the influence problem intensifies (proxied by firm characteristics) and as the quality of the public signal varies (proxied by industry characteristics). It is based upon a comparison of investment behavior of small divisions across multi-divisional firms. The second specifies investment levels given the attractiveness of the investment opportunity in the small division (i.e. division ‘type’ proxied by division future profits and Tobin’s Q of the industry) and is based on a comparison of investment behavior between small divisions of multi-divisional firms and stand-alone firms (acting as a proxy for first-best investment).

The second set of implications about investment levels are relatively easy to derive, however, there are some drawbacks associated with this approach. First, there are difficulties with using stand-alone firms to represent a benchmark for first-best investment levels. Second, proxies for investment opportunity also have limitations. Division Q’s cannot be calculated. Hence, median Q of stand-alone firms in the industry in which the division operates is used as a proxy for divisional investment opportunity. However, this measure doesn’t take into account division-specific opportunities. Because of these reasons, coupled with the desire to develop an explicit test for the model’s signal-jamming and capital budgeting concepts, this paper focuses on the first approach, namely, small division investment sensitivities to public signals about investment opportunities.

3.1 Investment Sensitivity to the Public Signal as the Influence Problem Intensifies

The investment sensitivity analyses require some additional model derivations. Hence, a brief discussion of the observables and the estimable equation will make it easier to follow the logic of the empirical strategy. The analyses of investment sensitivities involve estimating an investment equation for the small division using least squares regression. I do not observe the private signal or the corruption parameter, but I do observe division investment, division profitability (which proxies for the public signal), and firm characteristics (which proxy for the corruption parameter). I regress investment in the small division on lagged profits of the small division while specifying the regression coefficient as a function of firm characteristics. Since the predicted value of a least squares regression can be interpreted as a conditional mean, the dependent variable can be expressed as expected investment conditional upon the realization of the public signal. The general form of the regression equation is as follows:
\[ E(K^S | \Pi^S) = \beta_0(\phi(\Omega)) \cdot \Pi^S + \beta_1 Z \]  

(11)

where \( K^S \) is investment in S in the current period, \( \Pi^S \) is the public signal proxied by lagged profits of S, \( Z \) represents other controlling variables which also contain information about division investment opportunities, and \( \phi \) is the corruption parameter proxied by \( \Omega \), a vector of observable firm characteristics.

But, how is this investment equation related to the model’s predictions? The regression coefficient \( \beta_0 \) measures the change in conditional investment due to a change in the public signal, i.e. the sensitivity of investment to the public signal. However, the model’s investment rules (Table 1) are stated in terms of levels of investment. In order to link the regression equation directly to the model in a manner consistent with the concept of capital budgeting incentives, I derive the sensitivity of expected investment to the public signal as a function of the corruption parameter, i.e. how investment changes due to a change in the public signal as \( \phi \) varies. This sensitivity can then be measured by estimating the coefficient \( \beta_0 \) in the above regression.

In the remainder of the paper, since the private signal is unobservable, I focus on small division investment sensitivity to the public signal for the first-best contract and the two optimal contracts from the model (OC1 and OC2 in section 2.5) and evaluate this sensitivity as a function of the corruption parameter (or the severity of the influence problem). Three distinct patterns of investment behavior emerge. (1) In the first-best contract (i.e. in the absence of influence activities), investment sensitivity to the public signal is not a function of the severity of the influence problem. (2) In the contract in which headquarters deters corruption (OC1), investment sensitivity to the public signal is an increasing function of the severity of the influence problem. (3) While in the contract in which headquarters allows corruption for moderate problems, but deters corruption for weak and severe problems (OC2), investment sensitivity to the public signal is an “N-shaped” function of the severity of the influence problem.

In the remainder of this section (Section 3.1), I derive small division investment sensitivity for the first-best contract and for the value-maximizing investment rules for the uncorrupted and corrupt actions from Table 1. Subsequently, I derive investment behavior implied by the two optimal contracts (second-best) and summarize the results in Figure 3 (Section 3.1ii). Next, I describe small division investment behavior implied by the optimal contracts as a function of the
public signal quality (as opposed to the severity of the influence problem) and summarize results in Figure 4 (Section 3.2). Finally, I derive the model's second set of implications i.e. the comparison of investment levels (given the underlying investment opportunity) between small divisions of multi-divisional firms and stand-alone firms (Section 3.3).

3.1i Investment Sensitivity to the Public Signal for First-Best, Uncorrupted and Corrupt Actions

The regression coefficient in the investment equation (11) measures sensitivity of investment to the public signal. Let $S_\Pi$ represent this sensitivity which can be defined as the change in expected investment (averaging over the private signal realizations) given the public signal due to a change in the public signal i.e.

$$S_\Pi = \frac{\Delta E(K^S | \Pi^S)}{\Delta \Pi^S}$$

In order to derive the relevant investment behavior for the empirical analysis, first I calculate expected investment levels in $S$ (taking expectations over the private signal) conditional upon public signal realizations and then evaluate the changes in expected investment as the public signal changes. Second, I evaluate how this sensitivity varies as the corruption parameter varies. Investment sensitivity to the public signal as a function of the corruption parameter is derived for the first-best contract, uncorrupted action and corrupt action. An outline of these derivations is in section 4 of the technical appendix (under separate cover) and the results are summarized below.

In the first-best contract there is no influence problem and investment sensitivity to the public signal is not a function of the corruption parameter. However, to induce the uncorrupted action, investment sensitivity to the public signal is a convex, increasing function of the corruption parameter (figure 1 below). This suggests that as managers find it easier to influence, headquarters makes investment less sensitive to the private signal (the signal managers can jam) in order to satisfy incentive compatibility and more sensitive to the public signal. In other words, they offer “lower-powered incentives” or incentives with lower sensitivity to the private signal.
In contrast, to induce the corrupt action, investment sensitivity to the public signal is more complicated due to the linear returns assumption and the resulting switch in investment strategy at the critical value of the corruption parameter. In the corrupt action, investment sensitivity to the public signal is a decreasing, linear function below $\phi_c^*$ and an increasing, linear function above $\phi_c^*$ (figure 2 below). The difference in investment behavior below this critical value versus above is caused by the switch of investment levels in the mixed-signal state $(\sigma_b, \Pi_g)$ between the two cases of public signal qualities. While neither investment rule is a function of $\phi$ (see Table 1), the probabilities associated with expected investment are. Thus, the underlying statistical properties of the model result in decreasing investment sensitivity to the public signal when public signals are relatively less informative than private signals (low quality public signal) and increasing investment sensitivity when the opposite holds.
3.1ii First-Best and Optimal Contracts--Investment Sensitivity to the Public Signal

In the previous section, I described small division investment behavior for the first-best contract, uncorrupted action and corrupt investment rules. In this section, I combine these results for the two optimal contracts which, in addition to the first-best contract, lead to three investment patterns for empirical evaluation (derived in Sections 3 and 4 in the technical appendix): (1) The first-best contract implies that investment sensitivity to the public signal is not a function of the severity of the influence problem. However, when firms suffer from influence problems, two patterns of investment behavior emerge. (2) Firms either deter corruption no matter how severe the influence problem, and investment sensitivity to the public signal is an increasing function of the corruption parameter (figure 3 below--Optimal Contract 1). (3) In contrast, firms allow corruption for moderate incentive problems, but deter corruption at the extremes. Investment sensitivity is a decreasing function for mid-range values of the corruption parameter (figure 2), but
an increasing function at the extremes (figure 1). This leads to an ‘N-shaped’ relationship (or non-monotonic relationship) between investment sensitivity to the public signal and the severity of the influence problem (figure 3 below—Optimal Contract 2).

**Figure 3**

**Small Division Investment Sensitivity to the Public Signal--Optimal Contracts 1& 2**

(as a function of the severity of the influence problem)

\[
S_{\Pi}^* = \frac{\Delta E(K^{S^*}|\Pi^S)}{\Delta \Pi^S}
\]

3.2 *Investment Sensitivity to the Public Signal as the Signal Quality Improves*

In this section, I repeat the derivation of the model’s implications outlined in the previous section (Section 3.1), but evaluate investment sensitivity to the public signal as the signal quality varies (as opposed to the influence problem intensifying). In a first-best world without influence activities, we would expect investment to be less sensitive to noisier signals. Consistent with a standard signal-extraction story, noisy signals are less informative and hence headquarters should place less importance on them as indicators of investment opportunities (i.e. investment sensitivity to signals is a monotonically increasing function of signal quality). However, in the presence of
influence activities, investment sensitivity to signals may not necessarily increase as the quality of the signal improves. In fact, the model generally predicts that the relationship between investment sensitivity to signals and the signal quality in optimal contracts (second-best) is not monotonically increasing.\textsuperscript{32} As before, there are several cases depending upon parameter values which lead to four investment patterns for empirical evaluation (figure 4 below--details in Section 5 of the technical appendix).

\textbf{Figure 4}

\textit{Small Division Investment Sensitivity to the Public Signal} \((S_{\Pi}^*)\)

(as a function of the public signal quality)

| Pattern 1 | decreasing | Optimal Contract 2 |
| Pattern 2 | increasing | decreasing | Optimal Contract 2 |
| Pattern 3 | increasing | decreasing | increasing | Optimal Contract 1 |
| Pattern 4 | increasing | Optimal Contract 1 |

1/2 \(\psi\) \(1\) (quality of the public signal)

Note: Optimal contract 1 \textit{deters} influence for all levels of signal quality, while Optimal Contract 2 \textit{allows} influence for low levels of signal quality and \textit{deters} for high levels of signal quality. \(S_{\Pi}^* = \Delta E(K^S|\Pi^S) / \Delta \Pi^S\)

\textbf{3.3 Investment Level Conditional on Investment Opportunity}

The second set of the model’s implications involve the comparison of investment levels between small divisions of multi-divisional firms and stand-alone firms given the underlying investment opportunities. To derive the empirical implications for this set of analyses, I calculate expected investment conditional on type for each optimal contract and compare it to first-best investment (when the type is known). The first best contract implies that headquarters should invest all capital in small divisions with attractive investment opportunities (i.e. when S is a ‘good
type’) and no capital in small divisions with poor investment opportunities. However, in multi-divisional firms with influence activities, optimal contracts generally lead to lower investment in small ‘good’ divisions and higher investment in small ‘bad’ divisions relative to first-best investment. The implications for small division investment distortions relative to first-best for both optimal contracts are summarized in Table 3 below (details in Section 6 of the technical appendix).

<table>
<thead>
<tr>
<th>Optimal Contract</th>
<th>S is ‘bad’ type</th>
<th>S is ‘good’ type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Optimal Contract 1 (OC1)</td>
<td>overinvestment</td>
<td>underinvestment *</td>
</tr>
<tr>
<td>- <em>deter</em> corruption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Optimal Contract 2 (OC2)</td>
<td>overinvestment</td>
<td>underinvestment *</td>
</tr>
<tr>
<td>- <em>deter</em> corruption for weak and severe problems</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- <em>allow</em> corruption for moderate problems</td>
<td>overinvestment *</td>
<td>underinvestment</td>
</tr>
</tbody>
</table>

*First-best investment is possible. In deterring corruption, the high private cost case (\( \tilde{c} \)) leads to first-best investment, while in allowing corruption, the low quality public signal case (\( \psi \)) leads to first-best investment.

### 4. Empirical Evidence

The model suggests that influence activities in multi-divisional firms lead to inefficient investment relative to first-best and that certain types of multi-divisional firms are more vulnerable to influence problems. Specifically, the model implies that headquarters designs investment incentive contracts to address this problem which result in three testable implications about small division investment behavior. The implications developed in Section 3 are summarized below:
Implication 1: Multi-divisional firms’ investment in small divisions can be characterized by an increasing (Optimal Contract 1) or ‘N-shaped’ relationship (Optimal Contract 2) between investment sensitivity to lagged profits and certain firm characteristics (as proxies for the severity of influence problem) (Figure 3).

Implication 2: Multi-divisional firms’ investment in small divisions can be characterized by a non-monotonic relationship between investment sensitivity to lagged profits and certain industry characteristics (as a proxy for the quality of the public signal) (Figure 4).

Implication 3: Multi-divisional firms overinvest in ‘bad’ small divisions and underinvest in ‘good’ small divisions in comparison to investment of stand-alone firms investment behavior (Table 3).

In this empirical results section, first I describe the data and summary statistics (Section 4.1). Subsequently, I discuss the empirical strategy, describe proxies, and present the results of the analyses based on investment sensitivities to the public signal (Section 4.2). First I conduct the analyses as a function of the severity of the influence problem (proxied by firm characteristics) and then as a function of the quality of the public signal (proxied by industry characteristics). Finally, I discuss the empirical strategy, describe proxies, and present the results of the analyses based on investment levels (Section 4.3).

4.1 The Data

The primary data set used in this analysis is the Compustat Industry Segment (CIS) database. 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, the paper uses 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 upon two samples: stand-alone firms (or single-segment firms) that operate in manufacturing industries (i.e., SIC codes from 2000 to 4000) and multi-segment firms with at least two segments that operate in manufacturing industries. The model distinguishes between two types of divisions
within the firm: (i) large, established divisions with known returns and (ii) smaller, newer divisions with unknown returns. 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). 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). In order to identify the extremes in investment behavior and maintain consistency with the model, only the largest and smallest segments in manufacturing industries are included in the analysis. Firms reorganize their segments over time leading to a potential selection problem in creating a panel. Partly due to this matching problem, but primarily because of the simple one-period framework of the model, the paper’s analyses are cross-sectional. 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. Table 4 (below) provides descriptive statistics of the key financial variables at both the firm and segment levels for the multi-segment firm sample and the firm level for the stand-alone firm sample.
Table 4

Descriptive financial statistics for samples of multi-segment firms and stand-alone (single segment) firms

<table>
<thead>
<tr>
<th>Sample Characteristics</th>
<th>Multi-segment Firms</th>
<th>Smallest Segments</th>
<th>Largest Segments</th>
<th>Stand-alone Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>Standard Deviation</td>
<td>Median</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Sales ($millions)</td>
<td>544</td>
<td>10453</td>
<td>90</td>
<td>1242</td>
</tr>
<tr>
<td>Assets ($millions)</td>
<td>426</td>
<td>13827</td>
<td>63</td>
<td>1416</td>
</tr>
<tr>
<td>Net Invest. / Assets</td>
<td>.0048</td>
<td>.0373</td>
<td>-.0006</td>
<td>.0753</td>
</tr>
<tr>
<td>Oper. Income / Assets</td>
<td>.1301</td>
<td>.0990</td>
<td>.1063</td>
<td>.5887</td>
</tr>
<tr>
<td>Sales Growth</td>
<td>.0367</td>
<td>.1970</td>
<td>.0255</td>
<td>3.808</td>
</tr>
<tr>
<td>Observations</td>
<td>2927</td>
<td>2927</td>
<td>2927</td>
<td>2927</td>
</tr>
</tbody>
</table>

Note: Descriptive statistics for the sample of observations of multi-segment firms and standalone firms. Included are the manufacturing segments (SIC codes between 2000 and 4000) during the 1989-93 period. 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. Source: Compustat

4.2 Investment Sensitivity to Public Signals About Investment Opportunity--Implications 1 & 2

Optimal contracts in the presence of influence activities imply that investment sensitivity to public signals follows a specific pattern as the influence problem and the signal quality vary. In this section, I discuss the empirical strategy and present the results of the analysis based on investment sensitivity to the public signal about investment opportunities in the small division.
4.2i Empirical Strategy

Before detailing the empirical specification and results, I describe proxies for the public signal, the quality of the public signal, and the severity of the influence problem. Problems with these and alternative proxies are discussed in Section 6 (Limitations and Robustness). I use lagged segment profits (operating income/assets) as a proxy for the public signal for several reasons: (i) segment Q’s cannot be calculated and industry Q’s do not reflect segment-specific investment opportunities and (ii) due to persistence in profits, current profits are generally a reasonable predictor of future profits.\textsuperscript{41} To proxy the quality of the public signal (or the quality of segment profits as an indicator of segment type), I use the informativeness of profits in predicting firm value for the segment’s industry. Roughly speaking, earnings measures are a good signal about firm value (and firm investment prospects) in industries where accounting measurements of firm value are closely related to the market value of the firm. I use value relevance of earnings rankings by industry developed in Chang (1998) which relies on industry classifications described in Fama and French (1997) and categorize the industries into five groups with increasing levels of value relevance (designated by $\text{val}$).\textsuperscript{42} I then create dummy variables for these groups to represent the quality of segment profits as a signal for segment investment opportunities. These groups are used as a proxy for the public signal quality parameter ($\Psi$) which is continuous and ranges from one-half to one (details in Table A2 of the appendix at the end of this paper).

In order to develop a proxy for the severity of the influence problem, the empirical strategy is to argue that specific firm characteristics ($\Omega$), such as degree of diversification, organizational structure, and financial strength make some firms more vulnerable to the large division manager’s action. If the firm is more focused (or less diversified) and the businesses of the divisions are closely related, the large division manager should be better informed about the small division’s investment prospects. Headquarters is more likely to listen to the large division manager about investment opportunities in S the more he knows about S’s business. Hence, L’s ability to corrupt the private signal and influence H’s decision is greater in firms with more closely related businesses. For example, IBM’s CEO might listen to the mainframe division manager’s opinion about 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, I expect more focused firms (or less diversified firms) with divisions
that operate in related businesses to be more vulnerable to influence activities (i.e. exhibit higher corruption parameters).\textsuperscript{43}

Second, if the firm has more divisions and a flatter hierarchy, the CEO and the members of the investment committee have broader responsibilities and may have less knowledge of and may be less discerning in evaluating the small division’s investment prospects. Or said differently, there is more noise in the information of the organization with more divisions. For example, since General Electric’s CEO and investment committee make investment decisions concerning ten business segments, their knowledge of each division and their ability to thoroughly evaluate investment opportunities is more limited. This is in contrast to a firm with two divisions, in which the investment committee’s opinion might be more difficult to influence. Again, it is argued that it is easier for the large division manager to corrupt the signal, and I expect firms with a greater number of divisions (or with flatter organizational hierarchies) to be more vulnerable to influence activities (i.e. exhibit higher corruption parameters).

Finally, if capital is unlimited at the firm level, division managers don’t compete for a share of a fixed capital budget. However, if capital is somewhat constrained, the large division manager has the incentive to influence headquarters’ capital allocation decision to get a larger share. Hence, I expect capital constrained firms to be more vulnerable to influence activities.

In order to proxy the corruption parameter with the above firm attributes, measures for degree of business relatedness, organizational hierarchy, and capital constraints need to be delineated. To measure the relatedness of division businesses, I compare SIC codes for the small and large divisions and designate five degrees of business relatedness. If the division SIC codes are different at the 1-digit level, the firm is highly unrelated (i.e. diversified firms). If the division SIC codes are the same at this level, the businesses are slightly related. If the division SIC codes are the same at the 2-digit level, the businesses are more related. Firms are highly related (i.e. focused firms) if the division SIC codes are the same at the 4-digit level.\textsuperscript{44} The flatness of the organizational hierarchy is simply measured by the number of segments. The number of segments in multi-divisional firms range from two to ten segments. Since there are five categories of business relatedness and nine categories of number of segments, both of these characteristics are used as proxies for the corruption parameter which is continuous and ranges from zero to one. Descriptive statistics for
To identify capital constrained firms, I use access to the public debt markets as the criterion. Firms that have access to the public debt markets are considered to be financially unconstrained, while those that have no access are considered financially constrained.\textsuperscript{45} The split in the sample for the capital constraint characteristic is approximately two-thirds constrained firms and one-third unconstrained firms. Not surprisingly, unconstrained firms have more segments than constrained firms.\textsuperscript{46} However, there is no significant difference in the relatedness characteristic between unconstrained and constrained firms.

4.2\textit{ii Empirical Specification and Results--Severity of the Influence Problem--Implication 1}

In this section, an investment equation for small segments is specified and estimated to evaluate whether firms in the sample exhibit a pattern of investment sensitivity that suggests that the allocation of capital is affected by influence activities. First, I evaluate whether or not firm characteristics as a measure of the severity of the influence problem have any effect on segment investment sensitivity to profits. Second, I evaluate whether the relationship between investment sensitivity to profits and firm characteristics is similar to the pattern associated with either alternative hypothesis (i.e. either an increasing or ‘N-shaped’ function of firm characteristics). While the ex ante contract is unknown, I do observe ex post investment and profits of the small segment and the relevant characteristics of the firm. Using OLS, I essentially regress investment in the small segment in the current period (denoted by \( K^S \)) on profitability of the small segment in the previous period (denoted by \( \Pi^{-1}_S \)) while specifying the coefficient to be a function of firm characteristics (\( \Omega \)). Specifically, I assume the coefficient on \( \Pi^{-1}_S \) to be a linear function of the firm characteristics. The general form of the regression equation is as follows:

\[
K^S = \beta_0(\Omega) \cdot \Pi^{-1}_S \quad \text{where} \quad \beta_0(\Omega) = \gamma_0 + \gamma_1 rel + \gamma_2 ndiv + \gamma_3 cap
\]  

\textsuperscript{(12)}
where rel, ndiv, and cap are dummy variables which are interacted with profitability and represent the degree of relatedness between segment businesses, the number of segments within the firm, and the degree of capital constraints, respectively.

The coefficient $\beta_0$ measures segment investment sensitivity to profits as a function of firm attributes. This component of the specification evaluates the model’s implications about segment investment sensitivity to the public signal as a function of the severity of the influence problem. The significance of this coefficient suggests how important public information about the segment’s investment opportunities is in determining investment. However, I also include other elements of the information set which are informative about the segment’s investment opportunities. Specifically, I include firm profitability and firm sales growth relative to the industry as measures of firm (or other segment) investment opportunities. Lastly, I control for industry and timing differences. The regression equation that is estimated is the following:

$$K_i^S = (\gamma_0 + \gamma_1 rel + \gamma_2 ndiv + \gamma_3 cap)\Pi_{i-1}^{S} + \beta_1 \Pi_{i-1}^{F} + \beta_2 X_i^F + \alpha_i + \delta_t + \epsilon_i$$  \hspace{2cm} (13)

where $K_i^S$ is the ith segment’s net capital expenditures (capital expenditures less depreciation) in period t divided by the book value of the ith segment’s assets in that period; $\Pi_{i-1}^{S}$ is the ith segment’s operating income in period t-1 divided by the book value of the ith segment’s assets in that period; $\Pi_{i-1}^{F}$ is identical to the previous variable except calculated for the firm containing the ith segment, and $X_i^F$ 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 ith segment); $\alpha_i$ is an industry dummy variable for the ith segment’s business defined at the 2-digit SIC level, $\delta_t$ is a year dummy variable, and $\epsilon_i$ is a disturbance term.

First, I determine whether or not firm characteristics which proxy for the severity of the information problem have any effect on segment investment. In order to do this, the dummy variables are tested in a series of nested models by imposing a greater number of restrictions. The most general model presented in this paper uses ten dummy variables to represent business relatedness and organizational hierarchy characteristics (model 1 of Table 5 below). Five dummies
are used to distinguish between the levels of business relatedness and five dummies to identify
different organizational hierarchies. First, let $rel = \{rel0, rel1, rel2, rel3, rel4\}$ denote a vector of
dummies in which $rel0$ equals 1 if the segments are highly unrelated (i.e. different at the 1-digit
SIC level) and the remaining $rel$ categories equal zero otherwise (i.e. $rel1$, $rel2$, $rel3$ and $rel4$). The
same holds true for all other dummies in the vector for higher degrees of business relatedness.
Specifically, $rel4$ equals 1 if the segments are highly related (i.e. the same at the 4-digit SIC level)
and the remaining $rel$ categories equal zero otherwise (i.e. $rel0$, $rel1$, $rel2$ and $rel3$). Next, let
$ndiv = \{ndiv2, ndiv3, ndiv4, ndiv5+, ndiv8+\}$ denote a vector of dummies in which $ndiv2$ equals 1
if the number of segments is equal to two and the remaining $ndiv$ categories equal zero otherwise.
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.\textsuperscript{47} Let $rel0$ and $ndiv2$ be the base
categories and, as such, they are excluded from the regression. I denote $cap$ as a dummy variable
which equals 1 if the firm is capital constrained (i.e. if it has no access to public debt markets) and
zero otherwise. I compare the general model (model 1) to a more restricted one (model 2) which
restricts all relatedness coefficients ($rel$) and number of division coefficients ($ndiv$) to be equal to
zero. The results are presented below in Table 5.
### Table 5

Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics Modeled by OLS Investment Equation

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Investment Sensitivity (t-stat)</th>
<th>Model 2</th>
<th>Coeff. (t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coef. (t-stat)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Pi_{-1}^S ) (segment oper. inc./assets)</td>
<td>.0650 ( 3.52)</td>
<td>.0650 ( 3.52)</td>
<td>.0288 ( 2.17)</td>
<td></td>
</tr>
<tr>
<td>( rel1 ) (same 1-digit SIC)</td>
<td>.0109 ( 0.82)</td>
<td>.0759 ( 4.68)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( rel2 ) (same 2-digit SIC)</td>
<td>-.0493 (-3.72)</td>
<td>.0157 ( 0.91)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( rel3 ) (same 3-digit SIC)</td>
<td>-.1061 (-4.09)</td>
<td>-.0411 (-1.45)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( rel4 ) (same 4-digit SIC)</td>
<td>-.0261 (-1.93)</td>
<td>.0389 ( 2.76)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( ndiv3 ) (3 segments)</td>
<td>-.0235 (-2.35)</td>
<td>.0415 ( 2.29)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( ndiv4 ) (4 segments)</td>
<td>-.0215 (-1.85)</td>
<td>.0435 ( 2.46)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( ndiv5+ ) (5,6 or 7 segments)</td>
<td>-.0496 (-2.40)</td>
<td>.0154 ( 0.65)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( ndiv8+ ) (8,9 or 10 segments)</td>
<td>-.0143 (-0.17)</td>
<td>.0507 ( 0.60)</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>( cap ) (capital constrained)</td>
<td>-.0321 (-2.35)</td>
<td>--</td>
<td>-.0362 (-2.70)</td>
<td></td>
</tr>
<tr>
<td><strong>Coef. (t-stat)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Pi_{-1}^F ) (firm oper. inc./assets)</td>
<td>.0411 ( 2.61)</td>
<td>--</td>
<td>.0559 ( 3.62)</td>
<td></td>
</tr>
<tr>
<td>( \chi^F ) (relative firm sales growth)</td>
<td>.0421 ( 5.89)</td>
<td>--</td>
<td>.0396 ( 5.44)</td>
<td></td>
</tr>
</tbody>
</table>

| Observations | 2927 | -- | 2927 |
| R-sq.        | .1008 | -- | .0623 |

Notes: (1) Model 1 includes (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 more segments representing flatter organizational structures with ndiv2 as the base category and (iii) cap equals 1 if firms have no access to the public debt markets (financially constrained) and zero otherwise (unconstrained) (2) Investment sensitivity to profits for each characteristic is calculated by summing the coefficient on \( \Pi_{-1}^S \) (which represents sensitivity for the base categories -- rel0 and ndiv2) and the coefficient for each category in model 1 (3) The restrictions in model 2 can be rejected at 1% level of significance. (4) Relative firm sales growth is defined as the deviation of the firm sales growth from the firm’s industry sales growth (2-digit SIC).

Since I can reject the restrictions in model 2 compared to model 1 at the 1% level of significance (p-value close to 0), I conclude that firm characteristics are important determinants of investment behavior of smaller segments. However, this rejection alone is not informative about...
the effects of influence activities. The test of whether investment is consistent with the first-best contract (or the null hypothesis that influence activities are absent) is the joint test that all coefficients on firm attributes are equal. If I can reject the null hypothesis (i.e. accept that the coefficients are different) and find a pattern which is consistent with that predicted by the optimal contracts (or the alternative hypotheses), then I have evidence which supports the effect of influence activities on investment behavior.

Next, I evaluate whether the relationship between investment sensitivity to profits and firm characteristics is similar to either pattern associated with the two optimal contracts (figure 3 in Section 3.1). Specifically, I look for evidence of either an increasing relationship between investment sensitivity to the public signal and the severity of the influence problem (optimal contract 1), an “N-shaped” relationship (optimal contract 2), or a combination of both.

In order to evaluate whether investment behavior is consistent with either optimal contract, I compare investment sensitivity to profits for all relatedness and number of segment categories in model 1 (calculated by summing the coefficient on $\Pi_{-1}^S$ and the coefficient for each category in Table 5). For example, to get investment sensitivity to profits for firms that operate in related businesses at the 2-digit SIC level, I sum the coefficient on $\Pi_{-1}^S$ (.0650) and the coefficient on $rel_2$ (-.0493) to get .0157. I repeat this calculation for all relatedness and number of segment categories (presented as investment sensitivity in Table 6). Next, to evaluate how investment sensitivity to the public signal changes as the influence problem becomes more severe, I make successive pairwise comparisons of sensitivity to profits by category of firm characteristic. Specifically, I evaluate how investment sensitivity changes as firm operations become more related and hierarchies become flatter. For example, in Table 6, investment sensitivity declines when comparing firms that operate in somewhat related businesses (.0157 for $rel_2$) to more related businesses (-.0411 for $rel_3$). In order to test whether the evidence supports either alternative hypothesis, 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 an increasing or “N-shaped” function of firm characteristics.
Table 6
Small Segment Investment Sensitivity to Profits and Changes Between Categories of Firm Characteristics

<table>
<thead>
<tr>
<th>Firm Characteristics</th>
<th>Investment Sensitivity (t-stat)</th>
<th>Differences in Investment Sensitivity Between Categories (t-stat)</th>
<th>Direction of Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>rel0 (different 1-digit SIC)</td>
<td>.0650 (3.52)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>rel1 (same 1-digit SIC)</td>
<td>.0759 (4.68)</td>
<td>rel1 - rel0 = .0109 (0.82)</td>
<td>↑</td>
</tr>
<tr>
<td>rel2 (same 2-digit SIC)</td>
<td>.0157 (0.91)</td>
<td>rel2 - rel1 = -.0602 (-6.79)</td>
<td>↓</td>
</tr>
<tr>
<td>rel3 (same 3-digit SIC)</td>
<td>-.0411 (-1.45)</td>
<td>rel3 - rel2 = -.0568 (-2.37)</td>
<td>↓</td>
</tr>
<tr>
<td>rel4 (same 4-digit SIC)</td>
<td>.0389 (2.76)</td>
<td>rel4 - rel3 = .0780 (3.24)</td>
<td>↑</td>
</tr>
<tr>
<td>ndiv2 (2 segments)</td>
<td>.0650 (3.52)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>ndiv3 (3 segments)</td>
<td>.0415 (2.29)</td>
<td>ndiv3 - ndiv2 = -.0235 (-2.35)</td>
<td>↓</td>
</tr>
<tr>
<td>ndiv4 (4 segments)</td>
<td>.0435 (2.46)</td>
<td>ndiv4 - ndiv3 = .0020 (0.20)</td>
<td>--</td>
</tr>
<tr>
<td>ndiv5+ (5, 6 or 7 segments)</td>
<td>.0154 (0.65)</td>
<td>ndiv5+ - ndiv4 = -.0280 (-1.35)</td>
<td>↓</td>
</tr>
<tr>
<td>ndiv8+ (8, 9 or 10 segments)</td>
<td>.0507 (0.60)</td>
<td>ndiv8+ - ndiv5+ = .0352 (0.41)</td>
<td>↑</td>
</tr>
</tbody>
</table>

Notes: (1) See note under Table 6 for description of firm characteristics (2) Investment sensitivity to profits for each characteristic is calculated by summing the coefficient on $\Pi - 1$ and the coefficient for each category in model 1 of Table 6 (3) Differences in investment sensitivity between categories is calculated by differencing investment sensitivity between successive pairs of categories; t-stats are the result of a test on the equality of coefficients between categories (4) Direction of change represents whether investment sensitivity is increasing or decreasing from one category to the next as firms exhibit characteristics which suggest increasing severity of influence problems.

The results in Table 6 suggest that the observed investment behavior is consistent with that predicted by optimal contract 2 (or a combination of both optimal contracts): investment sensitivity to the public signal is an ‘N-shaped’ function of the severity of the influence problem. Investment sensitivity to profits is increasing for firms with weak and severe influence problems and decreasing for moderate problems. First, focusing on the business relatedness variable, 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 (t-stats for differences between categories). While the same general pattern holds for the number of segments variable, the
differences are not significant. However, when I collapse categories and compare firms with two segments versus those with more than two segments, investment sensitivity decreases (-0.0245) and the difference is significant (t-stat of -2.62). This suggests that the number of segments may be important, but that the mapping between this variable and the corruption parameter may not be linear (as assumed). Investment sensitivity to profits for each category of firm characteristics and the resulting “N-shaped” function from Table 6 are illustrated in figure 5 below.48

Finally, I discuss the interpretation of the coefficients on the capital constrained dummy (cap) and the firm variables ($\Pi_{-1}^F, X^F$) in model 1 in Table 5. The negative sign on the capital constrained dummy suggests that capital constrained firms make segment investment less sensitive to public signals. This appears to be consistent with the explanation that the competition for funds is greater in financially constrained firms.49 Finally, the significance of the coefficients on the firm variables ($\Pi_{-1}^F, X^F$) suggests that segment investment is dependent upon firm (or other segment) investment opportunities. This is consistent with the finding in other empirical work that firms make investment decisions within the hierarchy and actively allocate capital across divisions.50

The empirical results presented in Tables 5 and 6 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 certain types of firms. Specifically, the results presented in Table 5 and 6 suggest that investment sensitivity to profits varies with firm characteristics in a way which is: (i) inconsistent with first-best investment (i.e. investment sensitivity to profits is not a function of firm characteristics in the absence of influence activities), and (ii) consistent with second-best optimal contracts (i.e. investment sensitivity to profits is an ‘N-shaped’ function of firm characteristics in the presence of influence activities).
Figure 5

Small Segment Investment Sensitivity to Profits for Categories of Firm Characteristics
Business Relatedness (rel) and Number of Divisions (ndiv)

(dotted lines represent standard error bands)

Severity of Influence Problem
(firm characteristics (Ω) as a proxy for φ)

Note: Severity of the influence problem is proxied by increasing levels of relatedness between small and large segments (rel-increasing from left to right) and by flatter organizational hierarchies (ndiv-measured by increasing number of segments).
In this section, first, I evaluate whether industry characteristics as a measure of the quality of the public signal have any effect on investment sensitivity to profits for the small segments. Second, I evaluate whether the relationship between investment sensitivity to profits and industry characteristics is similar to the pattern consistent with a simple signal-extraction story or that associated with influence activities. Specifically, is investment sensitivity to profits a monotonically increasing function of the quality of the public signal measured by industry characteristics (i.e. a signal-extraction story) or is it a non-monotonic function (i.e. the influence activities story exhibited in Figure 4)? This section follows the same procedure as the previous section. However, in the earlier investment equation (13), the coefficient on profits was a function of the severity of the influence problem (\( \phi \)) proxied by firm characteristics (\( \Omega \)). In this section, the coefficient is a function of the quality of the public signal (\( \psi \)) proxied by the informativeness of profits in predicting firm value in the segment’s industry (\( val \) measured by the value relevance of earnings). Specifically, equation (13) now becomes

\[
K_i^S = (\lambda_0 + \lambda_1 val)\Pi_{i-1}^S + \beta_1 \Pi_{i-1}^F + \beta_2 X_i^F + \alpha_i + \delta_i + \varepsilon_i
\]

(14)

where \( K_i^S \) is the ith segment’s net capital expenditures (capital expenditures less depreciation) in period t divided by the book value of the ith segment’s assets in that period; \( val \) is a vector of dummy variables which represent the informativeness of profits as an indicator of investment opportunity in the segment’s industry (categories are defined in Table A2); \( \Pi_{i-1}^S \) is the ith segment’s operating income in period t-1 divided by the book value of the ith segment’s assets in that period; \( \Pi_{i-1}^F \) is identical to the previous variable except calculated for the firm containing the ith segment, and \( X_i^F \) 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 ith segment); \( \alpha_i \) is an industry dummy variable for the ith segment’s business defined at the 2-digit SIC level, \( \delta_i \) is a year dummy variable, and \( \varepsilon_i \) is a disturbance term.
First, I determine whether or not the informativeness of earnings in predicting investment opportunity (val) which proxies for the quality of the public signal (ψ) has any effect on segment investment. I let val={val1, val2, val3, val4, val5} denote a vector of dummies in which val1 equals 1 if the informativeness of earnings about investment opportunities is low in the segment’s industry and the remaining val categories equal zero otherwise (i.e. val2, val3, val4 and val5). The same holds true for all other dummies in the vector for higher degrees of the informativeness of earnings about segment investment opportunities. Specifically, val5 equals 1 if the informativeness of earnings about investment opportunities is high in the segment’s industry and the remaining val categories equal zero otherwise (i.e. val1, val2, val3 and val4). Let val1 be the base category and, as such, it is excluded from the regression. The results of this model are presented in Figure 6 (detailed results in Table A3 of the included appendix).
Figure 6

Small Segment Investment Sensitivity to Profits for Categories of Industry Characteristics
Informativeness of Earnings as a Measure of Investment Opportunity (val)

(dotted lines represent standard error bands)

\[ \hat{\beta}_0(val) \]

Quality of Public Signal
(informativeness of earnings in predicting investment opportunities (val) as a proxy for \( \psi \))

Note: Quality of public signal is proxied by increasing informativeness of earnings as a predictor of segment
ingestment opportunities or type [value relevance of earnings (val) increasing from left to right].

The empirical results presented in Figure 6 suggest that investment behavior of small divisions
within multi-divisional firms is not consistent with a standard signal-extraction story and is
consistent with that predicted by the influence model for certain parameters. Again, these results
suggest influence activities are an important factor in how headquarters allocates capital to small
divisions and that the investment distortions relative to first-best are more pronounced in firms that
operate in less predictable industries (or in industries in which earnings are less informative about
investment opportunities). Specifically, the results presented in Figure 6 suggest that investment
sensitivity to profits varies with industry characteristics in a way which is: (i) inconsistent with a simple signal-extraction story (i.e. investment sensitivity to profits is not an increasing function of the quality of the public signal), and (ii) consistent with second-best optimal contracts (i.e. investment sensitivity to profits is a non-monotonic function of public signal quality in the presence of influence activities).

4.3 Investment Level Conditional on Investment Opportunity--Implication 3

The previous section (Section 4.2) evaluated investment sensitivity to public signals about investment opportunities across multi-divisional firms with different firm and industry characteristics (Implications 1 & 2). This section evaluates the predictions about investment levels summarized in Table 3 and Implication 3 by comparing investment behavior of small divisions of multi-divisional firms to that of stand-alone firms. Before detailing the empirical specification and results, I describe the empirical strategy and proxies for the division type (i.e. the attractiveness of investment prospects).

4.3i Empirical Strategy

The first-best contract implies that firms invest less in bad types and more in good types. This is consistent with neoclassical theory which states that investment is proportional to investment opportunities (which can be represented by discounted future profits and measured by Tobin’s Q). However, optimal contracts in the presence of influence activities lead to overinvestment in bad types and underinvestment in good types relative to first-best (Table 3 in Section 3.2 and Implication 3).

One way to evaluate whether there is evidence in favor of the model is to first classify small divisions in the multi-divisional sample by: (i) division type and (ii) investment level; and then determine whether the distribution is statistically different than that of the stand-alone firm sample. Specifically, given a bad type, do more multi-divisional firms invest at high levels relative to stand-alone firms? Similarly, given a good type, do fewer multi-divisional firms invest at low levels relative to stand-alone firms?

In order to answer these questions, I construct frequency tables for the two samples: (i) small segments of multi-segment firms and (ii) stand-alone firms (or single segment firms). I argue that
stand-alone firms represent first-best investment, or at minimum, they represent investment without influence activities between segments. The tables compare investment levels relative to median investment in the segment’s industry (designated ‘low’ or ‘high’ investment) to the attractiveness of the investment opportunity (designated ‘bad’ or ‘good’ type). The investment levels of small segments are compared to the median investment of small segments in the segment’s industry, while the investment levels of stand-alone firms are compared to the median investment of stand-alone firms in the firm’s industry. I use two proxies for small division type: the segment’s future profitability and the median Tobin’s Q for stand-alone firms in the segment’s industry (same 2-digit SIC). To determine a division’s investment opportunity using future profits, I rank all observations (stand-alone firms, small and large segments of multi-segment firms) by future profits (i.e. deviation of operating income divided by assets from industry medians, two-periods ahead). I classify the bottom third of the observations as ‘bad’ types and the top third as ‘good’ types (deleting the middle third which are most vulnerable to endogeneity problems). As an alternative proxy, I use median Q for stand-alone firms in the segment’s industry and designate ‘bad’ (‘good’) types as those segments that operate in industries with Q’s less than (greater than) a specified cutoff value (1.3).

4.3ii Empirical Specification and Results--Implication 3

Using future profits of the segment as a proxy for segment investment opportunity, first I find that stand-alone firms are more likely to invest at low levels given poor investment prospects (57% versus 43%) and more likely to invest at high levels given good investment prospects (59% versus 41%) (Table 7 below). This investment pattern is consistent with first-best (i.e. in the absence of influence activities). Second, I compare investment levels for multi-segment and stand-alone firms and find evidence supporting the presence of influence activities (i.e. investment behavior consistent with the model’s implications presented in Table 3). Specifically, I find that multi-segment firms are more likely to invest at high levels in small bad segments (53%) than stand-alone firms with poor investment opportunities (57%). In addition, multi-segment firms are more likely to invest at low levels in small good segments (55%) than stand-alone firms with good investment opportunities (59%). Hence, on average, I find that multi-segment firms invest more in small divisions with
poor investment opportunities (overinvest in bad) and less in small divisions with attractive investment opportunities (underinvest in good), relative to first-best.\textsuperscript{55}

Table 7
Frequency Tables for Small Segments of Multi-segment Firms and Standalone Firms

(\% of observations with low/high investment levels conditional upon type)

<table>
<thead>
<tr>
<th></th>
<th>Small Segments of Multi-segment Firms</th>
<th>Stand-alone Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bad type</td>
<td>Good type</td>
</tr>
<tr>
<td>Low Investment</td>
<td>53% *</td>
<td>45% *</td>
</tr>
<tr>
<td></td>
<td>(417)</td>
<td>(550)</td>
</tr>
<tr>
<td>High Investment</td>
<td>47% *</td>
<td>55% *</td>
</tr>
<tr>
<td></td>
<td>(376)</td>
<td>(681)</td>
</tr>
</tbody>
</table>

Note: Number of observations appear in parentheses. Low (high) investment for small segments defined as capital expenditure / assets in period t-1 lower (higher) than industry median (2-digit SIC) of small segments; similarly investment for stand-alone firms defined relative to industry median (2-digit SIC) of stand-alone firms. Bad (good) type defined as bottom (top) one-third of all observations (standalone firms, small and large segments) ranked by deviations in profits (operating income/ assets) from industry medians of stand-alone firms in period t+1. * represents significantly different \% than stand-alone firms at the 1\% level.

5. Limitations and Robustness

The paper’s main results are presented in Table’s 5 and 6 and Figure 5, which summarize the estimation and analysis of Model 1. Hence, I focus on the limitations and robustness of Model 1’s specification. First, one of the most important assumptions in the model is the larger, established division manager’s ability to influence private (or internal) signals about the smaller, newer division’s investment prospects. Empirically, I use relative division sales size to represent these two types of divisions. While tenure of the division manager is one (unavailable) measure of the ability to influence information, the use of relative division sales to represent the division manager’s informal power within the organization seems to be a reasonable proxy. However, since small
divisions do not necessarily operate in developing, less predictable businesses, the asymmetric assumption about uncertainty in investment returns (known returns for the large division and unknown for the small division) may not be reasonable.

Three observations suggest that the asymmetric returns assumption is reasonable. 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 (includes select 2-digit SIC codes: 28, 35, 36 and 37). Generally, the investment pattern still holds (compare columns 1 and 2 in Table A4 in the included appendix). That is, the coefficients on the business relatedness dummies are significantly different from one another and they exhibit an ‘N-shaped’ pattern. Second, the large segments in the sample are (slightly) more likely than small segments to be operating in industries in which earnings are better predictors of firm value (i.e. more predictable businesses). And finally, in the table of descriptive financial statistics (Table 4), small segment profitability exhibits a higher variance relative to large segment profitability. The latter two observations suggest there is more uncertainty in small segment returns than in large segment returns, which is consistent with the asymmetric return assumption.

The second limitation is due to the use of lagged profitability of the small segment as a proxy for the public signal about the segment’s investment prospects. As mentioned earlier, a forward-looking measure would be segment Q, however one drawback in using industry Q is that it doesn’t account for segment-specific opportunities. While the inclusion of industry Q in the regression equation suggests that industry opportunity is an important explanatory variable for segment investment, it has a negligible effect upon the results in Model 1 (compare columns 1 and 3 of Table A4 in the included appendix). 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 Q, and hence this may explain part of the pattern. If this were the case, it follows that segment investment should be more responsive to firm profits as segments become more related. However, when I interact firm characteristics with firm profitability, there is no evidence of this pattern and the pattern of coefficients on segment profits is generally stable (not reported).

The third limitation is that I treat the organization 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. By modeling the influence activities between only two divisions, I ignore potential influence between other divisions. However, I argue that the ability to influence is greatest between the largest and smallest manufacturing divisions and that the ability of manufacturing division managers to influence signals about non-manufacturing divisions is limited. By analyzing firms with only two divisions, the investment pattern still holds (compare columns 1 and 4 in Table A4 in the included appendix). Again, the coefficients on the business relatedness dummies are significantly different from one another and they exhibit an ‘N-shaped’ pattern.

Fourth, one may argue that the estimates of the coefficients 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 (refer to footnote 29).

Fifth, 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.

Finally, the results 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.
6. Conclusion

The contributions in this paper are important for several reasons. To date, empirical evaluation of incentive theory is quite limited, primarily due to the difficulty in testing model predictions because of data limitations. This paper links the implied small division investment behavior of capital budgeting incentives to observables in a large cross-section of multi-divisional firms. It focuses on the quality of information that headquarters uses to make investment decisions and division investment sensitivity to that information as the relative quality of private and public signals vary. By evaluating investment sensitivity to profits as a function of firm characteristics and as a function of the signal quality of profits, I find evidence that firms allocate capital across divisions in a way that suggests that influence problems are an important factor in the investment decisions of multi-divisional firms and that they lead to investment distortions relative to first-best investment.

The paper suggests that division managers in multi-divisional firms have the ability to influence signals about investment opportunities and thereby increase the capital allocated to their division. Headquarters can mitigate manager influence on signal realizations by incorporating incentive contracts into the capital budgeting process, but these optimal contracts lead to investment distortions. This paper evaluates three empirical implications about investment behavior of multi-divisional firms and finds that influence activities by division managers play an important role in the allocation of capital to small manufacturing divisions and that certain types of firms suffer more from investment distortions. First, investment sensitivity to profits for smaller divisions of manufacturing firms depends upon firm characteristics in a way that is consistent with the signal-jamming effect of influence activities. Specifically, as influence problems intensify (proxied by firm characteristics), firms which face moderate corruption problems decrease investment sensitivity to profits, while firms which face weak or severe problems increase investment sensitivity to profits (i.e. an “N-shaped” relationship). Second, the investment behavior of small divisions does not support the standard signal-extraction story in which investment sensitivity to profits increases as the signal quality of profits improve. Third, multi-divisional firms are more likely to invest more in small divisions with poor investment opportunities and less in small divisions with attractive opportunities relative to first-best. In summary, multi-divisional firms with-- operations in related businesses, flatter organizational hierarchies, tighter financial constraints, and operations in industries where profits are a poor signal of investment opportunity-- allocate capital in a way that
suggests they are more vulnerable to influence activities and suffer from greater investment distortions in their internal capital markets.

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. 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. 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. Part of General Motors success in developing Saturn may be attributed to its approach in treating Saturn as a separate entity, thereby taking advantage of the benefits of a multi-divisional firm while minimizing the costs of influence activities. Clearly, there is more work to be done to understand decisions by multi-divisional firms that determine firm boundaries.
Appendix--Tables

Table A1

Number of Firms with Different Attributes in Multi-segment Sample

<table>
<thead>
<tr>
<th>Relatedness of small and large segment businesses*</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</td>
<td>2</td>
<td>204</td>
<td>549</td>
<td>248</td>
<td>48</td>
<td>108</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>170</td>
<td>386</td>
<td>163</td>
<td>53</td>
<td>66</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>103</td>
<td>245</td>
<td>115</td>
<td>19</td>
<td>42</td>
</tr>
<tr>
<td>Number of segments** (ndiv)</td>
<td>5</td>
<td>40</td>
<td>135</td>
<td>46</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>17</td>
<td>57</td>
<td>27</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>7</td>
<td>7</td>
<td>10</td>
<td>5</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>9</td>
<td>6</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>7</td>
<td>6</td>
<td>3</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>557</td>
<td>1392</td>
<td>609</td>
<td>136</td>
<td>233</td>
<td>2927</td>
</tr>
</tbody>
</table>

* Firms that operate in businesses that are more related suffer from more severe influence problems.

** Number of segments as a measure of the flatness of the organizational hierarchy. More segments implies flatter hierarchy and more severe influence problem.
Table A2

**Categories of Value Relevance of Earnings (val)**

**Informativeness of Earnings in Predicting Firm Market Value**

(proxy for quality of the public signal (ψ))

<table>
<thead>
<tr>
<th>Category</th>
<th>Industries Included</th>
<th>Number and Percent of Observations (Small Segments)</th>
</tr>
</thead>
<tbody>
<tr>
<td>val1 (low)</td>
<td>Trading, Wholesale, Measuring Equipment, Pharmaceutical Products, Consumer Goods, Computers, Medical Equipment, Business Service</td>
<td>532 19.0 %</td>
</tr>
<tr>
<td>val2</td>
<td>Construction, Rubber Products, Fabricated Products, Printing and Publishing, Petroleum and Coal</td>
<td>342 12.2 %</td>
</tr>
<tr>
<td>val3</td>
<td>Machinery, Electronic Equipment, Food Products, Alcoholic Beverages, Recreational Products</td>
<td>691 24.6 %</td>
</tr>
<tr>
<td>val4</td>
<td>Electric Equipment, Construction Materials, Business Supplies, Chemicals</td>
<td>865 30.8 %</td>
</tr>
<tr>
<td>val5 (high)</td>
<td>Shipping Containers, Automobiles, Aircraft, Steel Works, Apparel, Textiles</td>
<td>376 13.4 %</td>
</tr>
</tbody>
</table>

Note: Value Relevance of Earnings (val) increasing from val1 to val5 is the inverse of the variation of the log of firm value measured by accounting measures divided by firm market value [Chang (1998)]. Specifically, the inverse of the variance of log (V/P) where P is the market value of the firm and V is firm value estimated from the accounting-based valuation model.
Table A3
Small Segment Investment Sensitivity to Profits as a Function of Industry Characteristics
Modeled by OLS Investment Equation

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coefficient (t-stat)</th>
<th>Investment Sensitivity (t-stat)</th>
<th>Differences in Investment Sensitivity Between Categories of Signal Quality (t-stat)</th>
<th>Direction of Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Pi_{-1}^S$ (val1)</td>
<td>.0049 (1.31)</td>
<td>.0049 (1.31)</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>(segment oper. income/assets)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>val2</td>
<td>.0229 (1.42)</td>
<td>.0278 (1.76)</td>
<td>$val2 - val1 = .0180 (-1.04)$</td>
<td>↑</td>
</tr>
<tr>
<td>val3</td>
<td>.0001 (0.01)</td>
<td>.0050 (0.52)</td>
<td>$val3 - val2 = -.0227 (-1.23)$</td>
<td>↓</td>
</tr>
<tr>
<td>val4</td>
<td>-.0415 (-6.76)</td>
<td>-.0366 (-7.43)</td>
<td>$val4 - val3 = -.0416 (-3.83)$</td>
<td>↓</td>
</tr>
<tr>
<td>val5 (high)</td>
<td>.0573 (3.53)</td>
<td>.0622 (3.92)</td>
<td>$val5 - val4 = .0988 (5.97)$</td>
<td>↑</td>
</tr>
<tr>
<td>$\Pi_{-1}^F$ (firm oper. inc./ assets)</td>
<td>.0509 (3.30)</td>
<td>--</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>$X^F$ (relative firm sales growth)</td>
<td>.0392 (5.32)</td>
<td>--</td>
<td>--</td>
<td></td>
</tr>
</tbody>
</table>

Observations 2628
R-sq. .0875

Notes: (1) Model 3 includes five value relevance of earnings dummies (val) representing increasing levels of quality of the public signal as an indicator of investment opportunity with val1 as the base category (2) Investment sensitivity to profits for each characteristic is calculated by summing the coefficient on $\Pi_{-1}^S$ and the coefficient on each dummy for each category (3) Relative firm sales growth is defined as the deviation of the firm sales growth from the firm’s industry sales growth. (4) Differences in investment sensitivity between categories is calculated by differencing investment sensitivity between successive pairs of categories; t-stats are the result of a test on the equality of coefficients between categories (5) Direction of change represents whether investment sensitivity is increasing or decreasing from one category to the next as industries in which segments operate demonstrate increasing value relevance of earnings.
Table A4
Robustness Tests for Model 1
Small Segment Investment Sensitivity to Profits as a Function of Firm Characteristics Modeled by OLS Investment Equation

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 Whole Sample Coeff. (t-stat)</th>
<th>High-growth Industry Sample Coeff. (t-stat)</th>
<th>Add industry Q Whole Sample Coeff. (t-stat)</th>
<th>Two Segment Firms Coeff. (t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Pi_{-1}^S ) (segment oper. inc./assets)</td>
<td>.0650 (3.52)</td>
<td>.0681 (2.19)</td>
<td>.0653 (3.54)</td>
<td>.0741 (2.17)</td>
</tr>
<tr>
<td>( rel1 ) (same 1-digit SIC)</td>
<td>.0109 (0.82)</td>
<td>.00097 (0.46)</td>
<td>.0108 (0.82)</td>
<td>.0357 (1.58)</td>
</tr>
<tr>
<td>( rel2 ) (same 2-digit SIC)</td>
<td>-.0493 (-3.72)</td>
<td>-.0605 (-3.22)</td>
<td>-.0494 (-3.72)</td>
<td>.0200 (0.76)</td>
</tr>
<tr>
<td>( rel3 ) (same 3-digit SIC)</td>
<td>-.1061 (-4.09)</td>
<td>-.2113 (-5.95)</td>
<td>-.1051 (-4.05)</td>
<td>.1933 (-3.73)</td>
</tr>
<tr>
<td>( rel4 ) (same 4-digit SIC)</td>
<td>-.0261 (-1.93)</td>
<td>-.0494 (-2.35)</td>
<td>-.0264 (-1.95)</td>
<td>-.0129 (-0.64)</td>
</tr>
<tr>
<td>( ndiv3 ) (3 segments)</td>
<td>-.0235 (-2.35)</td>
<td>-.0385 (-2.45)</td>
<td>-.0236 (-2.36)</td>
<td>--</td>
</tr>
<tr>
<td>( ndiv4 ) (4 segments)</td>
<td>-.0215 (-1.85)</td>
<td>-.0324 (-1.92)</td>
<td>-.0216 (-1.85)</td>
<td>--</td>
</tr>
<tr>
<td>( ndiv5+ ) (5,6 or 7 segments)</td>
<td>-.0496 (-2.40)</td>
<td>-.0462 (-1.50)</td>
<td>-.0486 (-2.35)</td>
<td>--</td>
</tr>
<tr>
<td>( ndiv8+ ) (8,9 or 10 segments)</td>
<td>-.0143 (-0.17)</td>
<td>-.2713 (-0.47)</td>
<td>-.0150 (-0.18)</td>
<td>--</td>
</tr>
<tr>
<td>( cap ) (capital constrained)</td>
<td>-.0321 (-2.35)</td>
<td>-.0140 (-0.59)</td>
<td>-.0322 (-2.36)</td>
<td>-.0559 (-1.90)</td>
</tr>
<tr>
<td>( \Pi_{-1}^F ) (firm oper. inc./assets)</td>
<td>.0411 (2.61)</td>
<td>.0484 (2.17)</td>
<td>.0401 (2.55)</td>
<td>.0022 (0.09)</td>
</tr>
<tr>
<td>( X^F ) (relative firm sales growth)</td>
<td>.0421 (5.89)</td>
<td>.0532 (5.04)</td>
<td>.0413 (5.75)</td>
<td>.0694 (6.68)</td>
</tr>
<tr>
<td>Q (segment industry median Q)</td>
<td>--</td>
<td>--</td>
<td>.0234 (2.60)</td>
<td>--</td>
</tr>
</tbody>
</table>

Observations | 2927 | 1285 | 2927 | 1157 
R-sq. | .1008 | .1540 | .1031 | .1329 

Notes: (1) Model 1 includes (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 more segments representing flatter organizational structures with ndiv2 as the base category and (iii) cap equals 1 if firms have no access to the public debt markets (financially constrained) and zero otherwise (unconstrained) (2) Relative firm sales growth is defined as the deviation of the firm sales growth from the firm’s industry sales growth (2-digit SIC). (3) High-growth industry sample includes those segments that operate in select 2-digit SIC codes: 28, 35, 36 and 37. (4) Q is defined as the median Q of standalone firms operating in the segment’s industry (2-digit SIC) and represents market value (market equity at calendar year end plus assets less book equity) divided by assets. (5) Two segment firms include those firms with only two segments.
Footnotes:

2. See Stein (1997) and Hubbard and Palia (1998) for arguments leading to higher firm value and Rajan, Servaes, and Zingales (1998), Scharfstein (1998), and Scharfstein and Stein (1996) for that leading to lower firm value.
3. “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’ 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.
4. Carroll (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 that “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.”
5. Meyer, Milgrom and Roberts (1992) suggest that divestiture is an organizational solution to influence activities by poor-performing businesses. Another type of solution is practiced by Hewlett-Packard. This company has a policy which allows divisions to pursue any R&D projects, but requires divisions to finance projects out of funds they generate themselves (Milgrom and Roberts (1992), p. 277).
6. Capital 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.
7. This is the same result as that discussed in Tirole (1992). While ‘high-powered incentives’ are sometimes optimal, they may not be in multi-agent settings.
8. Taggart (1987) documents capital rationing in practice, e.g. Gitman and Forrester (1977) report that 52% of survey respondents allocated a fixed annual budget among competing projects and Scapens 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.
9. These other members of the organization can be thought of as an investment committee comprised of division managers, and financial, technical and possibly other administrative executives. The committee’s primary purpose is to inform headquarters about S’s type. Rajan and Zingales (1997) define access to critical resources as a form of power inside the organization. This definition is broader than the standard definition of power as control rights.
10. In the empirical section of the paper, this public signal is proxied by the lagged profitability of S.
11. Let \( a \in \{a_u, a_c\} \) represent L’s action with \( a_u \) denoting no influence activities [“u” stands for “uncorrupted”] and \( a_c \) denoting the corrupt action [“c” stands for “corrupt”]. In addition, let \( C(a) \) be the private costs to L, which takes the value \( c \) if L chooses to corrupt and zero otherwise.
12. This ‘informal power’ is formalized as the division manager’s ability to successfully jam private signals and determines the severity of the influence problem for the firm.

13. 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.

14. 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 corruption associated with the private signal are independent.

15. The random variables include S’s type, the noise in the public signal, and whether influence activities by L corrupts the private signal that H observes.

16. I assume H offers incentive contracts with commitment. If they didn’t, their reputations would suffer and managers would ignore the contracts. In contrast, Rajan, Servaes and Zingales (1998) assume that investment cannot be contracted upon.

17. L’s type is known because it is the core division; however, there is some uncertainty about S’s type. It is assumed that when S is good, the return from investment in S is higher than the known return from L, and vice-versa, when S is bad, i.e. \( r^S_g > r^L > r^S_b > 0 \). In addition, the expected return from investment in S is equal to the known return from L, i.e. \( \theta \cdot r^S_g + (1-\theta) \cdot r^S_b = r^L \). While this assumption simplifies the algebra in finding the solution, the general form of the solution holds for less restrictive assumptions.

18. One justification for this assumption is that borrowing costs to raise additional capital exceed the expected investment return from S and the known return from L. The reason for this may be due to asymmetric information in the external capital market. Specifically, H has more information than lenders.

19. This would occur when the lending rate to external borrowers is below the expected investment return from S and the known return from L.

20. Headquarters may offset some of the vested interests by linking L’s compensation to S’s profits (or the profits of the firm). However, this would not completely solve the problem, unless the firm was sold to the division manager. The assumption that managers derive utility from the size of their division is consistent with the standard assumption that private benefits (e.g. perquisites) to the division manager are proportional to the division’s size.

21. The main results use firm characteristics as a proxy for the corruption parameter, hence, the optimal contracts are evaluated as a function of this parameter as opposed to the private cost parameter or the quality of the public signal. However, in the empirical section of the paper, I use the informativeness of earnings in predicting firm market value for the industry as a proxy for the quality of the public signal and evaluate the optimal contracts as a function of public signal quality (\( \psi \)).

22. The first-best contract is defined as that which is optimal in the absence of influence activities given capital budgets.

23. Observe this as a linear programming problem that is solved using the Simplex algorithm (outlined in section 1 of the technical appendix that is under separate cover). As is common in this type of model, the incentive compatibility constraint binds in equilibrium for the uncorrupted contract. Two cases emerge depending upon the level of private costs to L from corrupting, \( c \): one case for low private costs (\( \underline{c} \)) and the other for high private costs (\( \overline{c} \)).

24. Focusing on case 2 (high private costs), the uncorrupted investment rule leads to efficient investment in three of the four states. In both good private signal states, H knows S is good and invests \( \overline{K} \) in S and nothing in L. In the bad private, bad public signal state, H knows S is bad and invests nothing in S and \( \overline{K} \) in L. However, in the bad private, good public signal state, even though S is known to be bad, H invests a positive amount in S and less than \( \overline{K} \) in L. By committing to overinvestment in S when it is known to be bad, H reduces the investment in L and makes L indifferent to engaging in influence
activities. In case 1 with low private costs, it is harder to make L indifferent, so H distorts investment in both mixed-signal states.

25. Two cases emerge, one case for the low quality public signal (ψ) and the other case for high quality (ψ'). The two cases of the corrupt investment rule are identical for three of the four states. In the two good private signal states, H knows S is good because, by assumption, a corrupt action cannot generate a good private signal given a bad type. Hence, H efficiently invests K in S and nothing in L. However, in the two bad private signal states, since a corrupt action can generate a bad private signal given a good type, H doesn’t know S’s type. In the mixed-signal state, the relative quality of the public signal to the corrupt private signal becomes relevant to the investment decision. When both private and public signals are bad, the probability that S is good is low, thus H invests nothing in S and K in L. The difference between case 1 and case 2 occurs in the bad private, good public signal state. When the relative quality of the public signal to the private signal is high (case 2), the good public signal ‘outweighs’ the bad private signal and H commits to invest K in S and nothing in L. In contrast, when the relative quality of the public signal to the private signal is low (case 1), the opposite occurs. The relative quality of the public and private signals depends upon the relationship between the two parameters: ψ (the probability that the public signal is correct) and φ (the probability that corruption is successful and generates a bad private signal given a good type). For example, when the corruption parameter (φ) is large, the expected precision of the private signal will be low and the relative quality of the public signal will be high. The knife-edge case between cases 1 and 2 occurs when φ = (1 − ψ) / ψ, which is denoted by φ_c^*.

Given a bad private, good public signal state (σ_b,Π_g), and when the corruption parameter equals this critical value, the expected returns from investing either K or zero in S are equal.

26. Scharfstein (1998) uses stand-alone firms as a proxy for first-best investment. He considers the possibility that the market systematically undervalues (overvalues) good (bad) investment opportunities, making investment in stand-alone firms inefficient. Since he finds that conglomerates are generally not successful and enduring and that they become more like stand-alone firms over the duration of the empirical study, he concludes that stand-alone firms invest efficiently. However, he doesn’t consider that stand-alone firms may be more capital constrained relative to multi-divisional firms, which may lead to inefficient investment (see footnote 51).

27. I discuss these proxies at length in the empirical section.

28. Subsequently, I also derive the sensitivity of investment to the public signal as a function of the public signal quality parameter.

29. Note that expected investment (the dependent variable) is calculated by averaging over the private signal realizations. Hence, the correctly specified regression that maps exactly to the derived measure of investment sensitivity includes only the public signal as an independent variable and excludes the private signal (since it is accounted for in the dependent variable).

30. When the corruption parameter equals φ_c^*, the expected returns from the two cases of the corrupt investment rule are equal.

31. This can be explained by the probabilistic relationships between investment levels and public signal realizations. When the relative quality of the public signal is low (ψ) or when φ < φ_c^*, investment sensitivity to the public signal [S_ψ(φ)] is a decreasing function. As φ increases, there is a higher probability of an inaccurate private signal in the mixed-signal state (σ_b,Π_g) i.e. higher Pr(σ_b,Π_g|t_g). (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. In contrast, H invests K in S when the quality of the public signal is high. Therefore, the opposite implication holds when φ > φ_c^*. 
32. There is one exception. Investment sensitivity to the public signal as the signal quality improves is an increasing function in one out of eight cases: when the influence problem is severe (high $\phi$), the proportion of bad types is high (high $\theta$), and the private costs are high (high $c$).

33. 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.”

34. For example, General Motors Corporation reports three segments: Automotive Products, Financing and Insurance Operations (includes GMAC) and Other Products. Within the automotive products segment there are groups (e.g. vehicle group, automotive components group) and then divisions within groups (e.g. GMC Truck division, Chevrolet Motor division, and Cadillac Motor Car division in the vehicle group).

35. Empirical studies with a large number of observations from the segment data set typically treat segments as divisions e.g. Rajan, Servaes, and Zingales (1998) and Shin and Stulz (1996). Scharfstein (1998) analyzes a subset of firms and attempts to refine the definition of a division by grouping segments.

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

37. While this is a rough proxy, it seems reasonable when comparing summary statistics for small and large segments in the sample. In Table 4, there is more variation in the operating income/assets and sales growth measures for the small segments relative to the large segments. In addition, the small segments in the sample are more likely than large segments to operate in industries in which earnings are less informative about firm value (or investment opportunities) suggesting more uncertainty about small segment returns.

38. However, the results are generally robust when using manufacturing firms with only two segments.

39. Since 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 each 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, access to debt-markets were used to calculate firm variables such as sales growth, profits, and degree of capital constraints. 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.

41. For a discussion of current profits (or cash flow) as a good predictor of future profits refer to Gilchrist and Himmelberg (1998). There is measurement error in all proxies used: Industry Q’s and division future profits as proxies for type; lagged division profits as a proxy for the public signal about type. My approach is to select a proxy and then evaluate the robustness of the results using other proxies.

42. Value relevance of earnings is a concept developed in the accounting literature and is measured by the inverse of variation of the log of firm value measured by accounting measures divided by firm market value [Chang (1998)]. Specifically, the inverse of the variance of log ($V/P$) where $P$ is the market value of the firm and $V$ is firm value estimated from the accounting-based valuation model.
43. 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. In contrast to my results, Rajan, Servaes, and Zingales (1998) find evidence that investment distortions increase with the diversity of a firm’s businesses.

44. I have chosen to use the standard approach in the literature that is to designate increasing relatedness when segments operate in the same 1-digit, 2-digit, 3-digit, or 4-digit SIC codes. Other empirical work uses different techniques some of which try to identify both horizontal and vertical linkages between segments. Generally, these more refined measures are used on smaller data sets [e.g. Scharfstein (1998)].

45. 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 because it is a simple measure that is the least controversial. While it is possible to delineate several categories of capital constraints, due to the current controversy over identifying capital constrained firms, this level of refinement is difficult to justify.

46. For the entire sample, the split between firms that have two segments versus more than two segments is approximately 40% versus 60%. For unconstrained firms, the split is 25% versus 75% and for constrained firms, the split is approximately 45% versus 55%.

47. Specifically, \( n_{div5+} \) represents firms with 5, 6, or 7 segments and \( n_{div8+} \) represents firms with 8, 9 or 10 segments.

48. The observed investment behavior is consistent with that implied by optimal contract 2 in figure 3 of section 3.2, except at very low values of the corruption parameter. It may be that low values of the corruption parameter are not observed in the data. The observed investment behavior is also consistent with some firms offering optimal contract 1 and other offering optimal contract 2.

49. The model makes no specific predictions about the effect of capital constraints and this result may be subject to multiple interpretations.

50. 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.

51. As mentioned earlier, Scharfstein (1998) also uses stand-alone firm investment behavior to represent first-best investment. However, he compares both small and large divisions to stand-alone firms, which is more problematic because of the size differences between the average stand-alone firm and large divisions.

52. Investment in period \( t-1 \) will affect profits in period \( t+1 \). However, the magnitude of this effect should not transform bad types (bottom third of the observations) into good types and the good types (top third of the observations) into bad types. The middle third of observations will be most susceptible to endogeneity problems and hence I delete them from this analysis.

53. \( Q \) is defined as the median \( Q \) of stand-alone firms operating in the segment’s industry (2-digit SIC) and represents market value (market equity at calendar year end plus assets less book equity) divided by assets. While the cutoff value of industry \( Q \) of 1.3 is arbitrarily chosen, the results hold for various cutoff measures which designate bad and good types.

54. One limitation of designating stand-alone firms as first-best is that stand-alone firms are most likely more capital constrained than multi-divisional firms which may decrease the number of stand-alone firms able to invest more in good businesses and decrease the number able to invest more in bad businesses. If this is true, then this may explain why stand-alone firms are less likely to invest more in bad types and in good types relative to multi-divisional firms.

55. The result also holds using the other proxy for investment opportunity (i.e. industry median \( Q \)) and for various cutoff measures of industry \( Q \) to designate bad and good types.
56. Refer to Gilchrist and Himmelberg (1995) for a discussion of this problem and techniques to resolve it.
57. See Berger and Ofek (1995) for the findings on the conglomerate discount and Comment and Jarrell (1995) for the findings on corporate focus.
58. 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 some smaller firms have been successful with similar products (e.g. Veriphone) (based upon company interviews).
References:


