Evidence on the Dark Side of Internal Capital Markets

Oguzhan Ozbas
University of Southern California

David S. Scharfstein
Harvard Business School and NBER

This article documents differences between the Q-sensitivity of investment of stand-alone firms and unrelated segments of conglomerate firms. Unrelated segments exhibit lower Q-sensitivity of investment than stand-alone firms. This fact is driven by unrelated segments of conglomerate firms that tend to invest less than stand-alone firms in high-Q industries. This finding is robust to matching on industry, year, size, age, and profitability. The differences are more pronounced in conglomerates in which top management has small ownership stakes, suggesting that agency problems explain the investment behavior of conglomerates. (*JEL* D21, D23, G31)

There is wide variation in the way firms are organized. For example, in 2005, Anadarko, Murphy Oil, and Kerr-McGee were all engaged in oil and gas exploration and production (E&P). However, while E&P was Anadarko's only line of business, Murphy Oil was integrated downstream into oil refining and marketing, and Kerr-McGee had unrelated operations in titanium dioxide. This variation in organizational form suggests some important questions: Did Anadarko, Murphy Oil, and Kerr-McGee manage their E&P businesses differently because they were parts of different types of organizations? Did their performances differ as a result?

Answering these types of questions is a central goal of organizational economics. It is also central to corporate finance: mergers and acquisitions, divestitures, spin-offs, and management buyouts all change organizational structure in ways that are designed in part to affect firm behavior and performance. Indeed,

---

This article is an extensive reworking of "The Dark Side of Internal Capital Markets II: Evidence from Diversified Conglomerates," National Bureau of Economic Research Working Paper No. 6352. We are grateful to the National Science Foundation, the MIT Financial Services Research Center, the Harvard Business School Division of Research, the Walter A. Rosenblith Fellowship Fund, and the Marshall General Research Fund for financial support and to numerous seminar participants for their comments on the prior version of the article. Judy Chevalier, Robert Gertner, Julio Rotemberg, Henri Servaes, and Jeremy Stein provided very useful feedback on the prior version of this article, as did Michael Weisbach (the editor) and an anonymous referee on the present version. Send correspondence to Oguzhan Ozbas at the University of Southern California, Department of Finance & Business Economics, Marshall School of Business, University Park Campus, Building HOH 514, Mail Code: 0804, Los Angeles, CA 90089; telephone: 213-740-0781; fax: 213-740-6650. E-mail: ozbas@usc.edu

doi:10.1093/rfs/hhp071 Advance Access publication September 23, 2009

in 2006 Kerr-McGee spun off its titanium dioxide business to become focused on E&P and was then sold to Anadarko. Was this because Kerr-McGee's diversified structure was inefficient?

This article analyzes the relationship between organizational form and efficiency by comparing the investment behavior of stand-alone businesses to the investment behavior of businesses that function as part of a diversified conglomerate. Williamson (1975) suggests that the internal capital market of diversified firms might allocate capital more efficiently than the external capital market because top management of a diversified firm is better informed about investment opportunities than external investors. Along these lines, Gertner, Scharfstein, and Stein (1994) and Stein (1997) present models that identify circumstances under which internal capital markets lead to more efficient investment decisions. In particular, Stein (1997) argues that managers of stand-alone firms will be reluctant to cut investment when they have no good investment opportunities. An internal capital market comprised of multiple business lines allows managers to redeploy capital from divisions with poor investment opportunities to those with good investment opportunities without compromising the overall capital budget.

There is also a theoretical literature that suggests just the opposite—that internal capital markets function less efficiently than the external capital market. Scharfstein and Stein (2000) argue that when firms are composed of divisions with good and bad investment opportunities, rent-seeking behavior on the part of divisional managers will lead top management to overinvest in the weak division and underinvest in the strong division. Meyer, Milgrom, and Roberts (1992) and Rajan, Servaes, and Zingales (2000) make similar predictions.

Given the competing theories, the answer is ultimately an empirical one. Thus, we compare the investment behavior of stand-alone businesses (such as Anadarko) with comparable business segments of diversified companies (such as Kerr-McGee's E&P business). We start by estimating the responsiveness of capital expenditures to industry investment opportunities, as measured by industry Q. Our basic finding is that the investment of stand-alone businesses is more responsive to industry Q than is the investment of "unrelated" segments of conglomerate firms. This finding is driven mainly by the fact that unrelated segments of conglomerate firms tend to invest less than stand-alone firms in high-Q industries. This fact is robust to careful matching of unrelated segments to stand-alone firms based on size, profitability, and age.

The lower investment of unrelated segments relative to stand-alone firms in high-Q industries could be a symptom of underinvestment by unrelated segments or overinvestment by stand-alone firms. To distinguish between these two interpretations, we examine whether this finding is more pronounced in diversified firms with low management ownership. If it is the unrelated segments that are investing inefficiently, and not the stand-alone firms, we should find more pronounced differences in diversified firms with low management ownership. This is indeed what we find. The finding is in line with the prediction of

Scharfstein and Stein (2000), who argue that one must have agency problems both at headquarters and at divisions to give rise to the inefficient allocation of capital.

A number of other papers have presented evidence of inefficient internal capital markets. Lamont (1997) shows that when oil prices are high, the non-oil divisions of diversified oil producers seem to invest more than their industry peers. Shin and Stulz (1998) find similar evidence in a broader sample: small divisions of conglomerates invest more when other divisions have high cash flows, but the extent of their investment does not depend on Q. Rajan, Servaes, and Zingales (2000) find that when divisions are in low-Q industries relative to other divisions in a firm, they tend to invest more than their stand-alone counterparts, and they tend to invest less when they are in high-Q industries relative to others in the firm. Billett and Mauer (2003) find that firms that they deem to have more efficient internal capital markets are more highly valued. The results are also related to those of Gertner, Powers, and Scharfstein (2002), who show that when divisions of diversified conglomerates are spun off, their investment becomes more sensitive to industry Q.

We see three main contributions of our article relative to the existing literature: the measurement of relatedness, our matching procedure, and the identification of the role of management incentives. With respect to relatedness, we are careful to identify segments of diversified firms that are truly unrelated to other segments by using information in the Input-Output Benchmark Surveys of the Bureau of Economic Analysis. The surveys provide data on the flow of goods and services among industries and allow us to identify significant vertical and horizontal industry relationships (Matsusaka 1993; Fan and Lang 2000).[1] As we argue, it is important to identify segments that are unrelated to others to ensure that there are no transfer pricing and co-investment decisions that introduce more measurement error into the accounting data of diversified segments than those of stand-alone firms.

Our matching procedure is also an improvement over the existing literature, which typically just adds linear industry and profitability controls. Instead, we use matching estimators (as described by Abadie and Imbens 2007) to compare the investment behavior of diversified segments and stand-alone firms that are similar on the basis of size, age, and profitability. The advantage of this nonparametric approach is that unlike parametric approaches, it does not rely heavily on extrapolation—which is problematic when there is imperfect overlap in the covariate distributions of comparison groups, as there is with unrelated segments and stand-alone firms.

Finally, our article appears to be the first to show that there are differences in the functioning of internal capital markets based on management incentives. This finding provides support for the view that the results are not driven by

[1] We use six different surveys in total (1977, 1982, 1987, 1992, 1997, and 2002), each covering panel years starting the year of the survey and ending the year before the next survey. For panel years 1979–1981, we use the 1977 survey. For panel years 1982–1986, we use the 1982 survey, and so on.

spurious measurement issues but rather are tied to the workings of internal capital markets.

The rest of the article is organized as follows. In the next section, we describe our data sources and relatedness measure. In Section 2, we document the basic finding that stand-alone firms are more responsive to industry Q than are the unrelated segments of conglomerate firms. In Section 3, we show that this basic result is robust to industry, size, and age matching. In Section 4, we show that our findings are more pronounced for conglomerate firms in which management has only a small stake. Section 5 concludes the article.

1. Data

Our segment-level data come from Compustat segment files covering the period 1979–2006. For each segment, these files provide basic accounting information such as sales, assets, capital expenditures, operating profits, and depreciation along with a pair of Standard Industrial Classification (SIC) codes for the entire panel and a pair of North America Industry Classification System (NAICS) codes starting in 1990 and onward. As is standard practice, we cross-validate observations in the segment files with observations in the annual files and drop observations for which the sum of reported segment sales do not fall within 25% of total firm sales in the annual files. We further drop segments with (i) name “other,” (ii) primary SIC code equal to zero, (iii) incomplete accounting data (sales, assets, capital expenditure, depreciation, operating profits), (iv) anomalous accounting data (zero depreciation, capital spending greater than sales or assets, capital spending less than zero), (v) sales less than \$20 million in 1982 dollars using the Bureau of Labor Statistics producer price index for finished goods (WPUSOP3000). We also exclude from the analysis segments that operate in regulated industries, specifically Transportation (SIC codes 4000-4799), Telecommunication Service (4800-4899), Utilities (4900-4999), Banking (6000-6199), and Insurance (6300-6499).

To assess the functioning of internal capital markets, we compare unrelated segments of conglomerate firms with stand-alone (single segment) firms. We focus on the unrelated segments of conglomerate firms instead of their related segments for two reasons. First, the theories discussed in the introduction suggest that resource allocation inefficiencies will be greater in diversified firms. Second, from a practical empirical measurement perspective, transfer pricing and asset allocation make it difficult to accurately assign profits and capital to a particular segment. For example, a vertically integrated chemical manufacturer might source inputs for its downstream unit from its upstream unit at below market transfer prices (Eccles 1985), thus inflating downstream profits and deflating upstream profits relative to stand-alone chemical firms. Or, the upstream unit might add production capacity to meet the specific input needs of the downstream unit, as shown by Mullainathan and Scharfstein (2001) in their study of the chemical industry.

For the empirical validity of our approach, we need a reliable indicator of whether segments are related. The standard methodology classifies segments as unrelated if they are in different two-digit industries. However, there are many two-digit industries that are clearly related, and there are some three- and four-digit industries within two-digit industries that are not related. For example, SIC 13, Oil and Gas Extraction, is certainly related to SIC 29, Petroleum Refining and Related Industries. And, although they are both in SIC 28, SIC 281, Industrial Inorganic Chemicals (such as chlorine), is arguably not related to SIC 283, Drugs.

We use an alternative method, which builds on the relatedness measure of Matsusaka (1993) and Fan and Lang (2000). We first identify vertically related industries using data from the Input-Output Benchmark Surveys of the Bureau of Economic Analysis. Specifically, we assume that two input–output (I-O) industries are vertically related if one of the industries buys more than 10% of its inputs from the other industry or sells more than 10% of its outputs to the other industry (the Appendix provides further details). We then consider each segment within a firm and determine whether it is related to another segment within the firm by way of operating either in vertically related I-O industries or, alternatively, in the same I-O industry. Our unrelated sample consists of segments that we cannot relate to any other segment within the firm after systematically enumerating every possible within-firm pairwise connection.

Table 1 provides descriptive statistics on sales, assets, cash flow, capital expenditures, capital expenditures divided by sales, cash flow divided by sales, and lagged industry Q (as a result, our sample effectively starts in 1980). We measure cash flow as operating profits plus depreciation. This measure of cash flow is standard in the literature and does not adjust cash flow for taxes, working capital investments, and other factors because those data are not available. We winsorize the ratio of cash flow to sales at the 1% level in both tails to deal with extreme values. We define industry Q as the median bounded Q of stand-alone firms within the same I-O industry. In calculating stand-alone Q's, we follow the data definition of Kaplan and Zingales (1997), but bound it above at 10 to reduce the effect of potential measurement error in the book value of assets. Specifically, we compute bounded stand-alone Q as $MVA/(0.9BVA + 0.1MVA)$, where the book value of assets equals Compustat item 6 and the market value of assets equals the book value of assets plus the market value of common equity (item 25 times item 199) less the book value of common equity (item 60) and balance sheet deferred taxes (item 74).[2] Note that this simple market-to-book ratio definition of Q differs from the standard measure of Q in that we do not estimate the replacement cost of fixed assets nor adjust for taxes. Previous studies have shown that these adjustments are not essential (see Perfect and Wiles 1994).

[2] Bounding Q in this way has the same basic effect as winsorising Q at the extremes as described in Baker, Stein, and Wurgler (2003). None of the results change if we winsorize at the 99th and 1st percentiles of Q.

Table 1
Descriptive statistics

Sample: All industries	Stand-alone		Unrelated	
Segment level	Mean	SD	Mean	SD
Segment sales	779	3,778	1,150***	6,117
Segment assets	773	4,530	932***	4,483
Segment capital expenditure	44	223	68***	413
Segment cash flow	99	486	154***	740
Segment capital expenditure/sales	0.072	0.116	0.061***	0.098
Segment cash flow/sales	0.121	0.158	0.139***	0.135
Lagged industry Q	1.42	0.40	1.31***	0.37
Obs	61,081		13,186	
Sample: Manufacturing industries	**Stand-alone**		**Unrelated**	
Segment level	Mean	SD	Mean	SD
Segment sales	720	3,299	1,271***	6,909
Segment assets	700	3,301	990***	4,989
Segment capital expenditure	46	263	72***	461
Segment cash flow	103	515	166***	815
Segment capital expenditure/sales	0.059	0.072	0.046***	0.048
Segment cash flow/sales	0.108	0.124	0.126***	0.097
Lagged industry Q	1.43	0.41	1.29***	0.35
Obs	30,645		9,978	

Observations are by segment and year (Compustat segment files, 1980–2006). Segment cash flow is defined as segment operating profits plus segment depreciation. Segment sales, assets, capital expenditure, and cash flow are in millions of dollars. Industry definitions follow the Input-Output Benchmark Surveys of the Bureau of Economic Analysis. Industry Q in a given year is the median bounded Q of stand-alone firms in the industry. A segment is defined to be unrelated if it is not related to any other segment of the firm. Two segments are related if they operate in vertically related industries or the same industry. Mean comparison tests between stand-alone firms and unrelated segments are performed without the assumption of equal variance. Asterisks indicate statistical difference at the 10% (*), 5% (**), and 1% (***) levels using a two-tailed test.

As shown in Table 1, stand-alone firms are smaller than unrelated conglomerate segments on the basis of both sales (\$779 million vs. \$1150 million) and assets (\$773 million vs. \$932 million). These differences are statistically significant at the 1% level. Stand-alone firms appear to be less profitable than unrelated segments as measured by the cash flow to sales ratio (12.1% vs. 13.9%). In addition, stand-alone firms appear to operate in industries with better investment opportunities than those of unrelated segments; the median industry Q of stand-alone firms is 1.42 as compared with 1.31 for unrelated segments. The difference is statistically significant at the 1% level. All of these differences exist within the subsample of segments in manufacturing industries (I-O industries 13–64 covering SIC codes 2000–3999).

2. Panel Analysis

Our main objective in this section is to determine whether there are systematic differences in the investment behavior of stand-alone firms and the unrelated segments of conglomerate firms. For this purpose, we use standard investment regressions and focus on the Q-sensitivity of investment. We estimate variants of the following panel regression:

$$cxs_{i(j)t} = a_j + b_t + c_0 * U_{it} + c_1 * Q_{j,t-1} + c_2 * Q_{j,t-1} * U_{it} + d_1 * cfs_{it} + d_2 * cfs_{it} * U_{it}. \quad (1)$$

The dependent variable $cxs_{i(j)t}$ is the sales-normalized capital spending of segment i (operating in industry j) in year t. a_j and b_t are industry and year fixed effects, respectively. We follow the industry definitions of the Input-Output Benchmark Surveys. In some specifications, we include segment fixed effects instead of industry fixed effects. The purpose of including industry or segment fixed effects is to address the possibility that time-invariant (perhaps technology-driven) differences in investment levels among industries or segments may explain our results. We include year fixed effects to deal with changing tax regimes and changing state of the business cycle during our sample period.

In addition, U_{it} is an indicator variable equal to one for unrelated segments. We include both the direct and interaction terms of U_{it}. Our key explanatory variable $Q_{j,t-1}$, the median bounded Tobin's Q of stand-alone firms in industry j in year $t-1$, proxies for investment opportunities. Because our sample provides us with a cross-section of segments facing similar investment opportunities in a given industry j and year t, we compute robust standard errors that allow for correlated error terms at the industry-year level. We also include cfs_{it}, sales-normalized cash flow of segment i in year t. We normalize by segment sales instead of segment assets because firms may have more discretion in allocating assets across their segments than they have in allocating sales. Nevertheless, we obtain qualitatively similar results when we normalize our variables using segment assets instead.

Table 2 presents the results of our panel analysis for the full sample (columns 1 and 3) and the restricted sample of manufacturing industries (columns 2 and 4). In column 1, unrelated segments exhibit lower Q-sensitivity of investment than stand-alone firms, as evidenced by a statistically significant negative value of c_2 (-0.017), the coefficient on $Q_{j,t-1} * U_{it}$. This result continues to hold (-0.016) for the manufacturing subset in column 2. Moreover, c_0 is positive and statistically significant (0.017 and 0.010 in columns 1 and 2, respectively), indicating that unrelated segments invest more (less) than their stand-alone counterparts in sufficiently low-Q (high-Q) industries.[3] All of these results are robust to the inclusion of segment fixed effects, which we report in columns 3 and 4.

[3] Our sample includes segment observations with $Q_{j,t-1}$ as low as 0.47 and as high as 4.66. At both extremes, the difference in investment levels between unrelated segments and their stand-alone counterparts (as implied by $c_0 * U_{it} + c_1 * Q_{j,t-1} + c_2 * Q_{j,t-1} * U_{it}$) is statistically different from zero at the 1% level. Moreover, the breakeven $Q_{j,t-1}$ (at which investment by unrelated segments and stand-alone firms equals each other; about 1.00 in column 1 and 0.63 in column 2) is generally lower than the median $Q_{j,t-1}$ (1.40). Thus, the coefficient estimates imply that for our sample of unrelated segments, the underinvestment effect in high-Q industries is more prevalent than the overinvestment effect in low-Q industries.

Table 2
Q-sensitivity of investment: Unrelated segments and stand-alone firms

Sample	All (1)	Manufacturing (2)	All (3)	Manufacturing (4)
Lagged industry Q	0.025***	0.025***	0.026***	0.023***
	[0.003]	[0.002]	[0.003]	[0.003]
Lagged industry Q × Unrelated	−0.017***	−0.016***	−0.013***	−0.010***
	[0.003]	[0.003]	[0.003]	[0.003]
Cash flow/sales	0.115***	0.066***	0.007	−0.009
	[0.014]	[0.013]	[0.010]	[0.009]
Cash flow/sales × Unrelated	−0.028*	0.017	−0.037	−0.004
	[0.016]	[0.014]	[0.024]	[0.016]
Unrelated	0.017***	0.010***	0.017***	0.012**
	[0.005]	[0.003]	[0.005]	[0.005]
Industry F.E.	Yes	Yes	No	No
Segment F.E.	No	No	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R^2	0.385	0.101	0.749	0.611
Obs	74,267	40,623	74,267	40,623

Unrelated segments and stand-alone firms are compared (Compustat segment files, 1980–2006). Dependent variable is capital spending over sales. Industry definitions follow the Input-Output Benchmark Surveys of the Bureau of Economic Analysis. Industry Q in a given year is the median bounded Q of stand-alone firms in the industry. Columns 2 and 4 restrict the sample to manufacturing industries. Heteroskedasticity-robust standard errors are in brackets. Standard errors are corrected for clustering at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) levels.

These effects are also economically significant. Based on the estimates in column 1, at the means of all of the explanatory variables including $Q_{j,t-1}$ at 1.40, unrelated segments are predicted to invest at a lower rate than stand-alone firms (0.062 vs. 0.072). More interestingly, this difference increases with $Q_{j,t-1}$. A one-standard-deviation (0.40) increase in $Q_{j,t-1}$ to 1.80 increases the investment rate of unrelated segments by 0.003 to 0.065, while it increases the investment of stand-alone firms by 0.010 to 0.082. At this higher level of $Q_{j,t-1}$ the difference in investment rates is 0.015, while the difference is 0.010 at the mean.

In column 2, which restricts the sample to manufacturing segments, the difference between stand-alone firms and unrelated segments in their Q-sensitivity is much larger in percentage terms. In particular, at the means of all the variables including $Q_{j,t-1}$ at 1.40, unrelated segments invest at the rate of 0.047, while stand-alone firms invest at the rate of 0.058. At higher levels of $Q_{j,t-1}$ the difference is even larger—a one-standard-deviation (0.40) increase in $Q_{j,t-1}$ to 1.80 increases an unrelated segment's investment to 0.050, a modest increase of 0.003, while a stand-alone firm's investment increases by 0.010 to 0.068. At this increased level of $Q_{j,t-1}$, the difference of 0.018 is 26% of stand-alone investment.

In the rest of the article, we build on these results to address two further issues. First, we investigate whether the results are robust to matching on observable characteristics such as industry, size, and age. Second, we test whether agency-based theories such as that of Scharfstein and Stein (2000) can explain the observed low Q-sensitivity of investment of conglomerate firms.

3. Matching Analysis

We know from Table 1 that the unrelated segments of conglomerate firms are on average larger than stand-alone firms. It is possible that larger segments exhibit lower Q-sensitivity of investment because they face larger technological adjustment costs for some reason. If this is the case, it would be a mistake to attribute differences in the Q-sensitivity of investment to a shortcoming of internal capital markets. Moreover, there may be differences in Q-sensitivities across industries (perhaps because of differences in adjustment costs or in the importance of physical capital). If unrelated segments are more prone to operate in industries with low Q-sensitivity of investment, it would be wrong to attribute our findings to the effects of internal capital markets. Similarly, there may be differences between young and old firms.

To address these problems, we form matched samples of unrelated segments and stand-alone firms based on observable characteristics such as industry, year, age, and size that are *a priori* important determinants of investment. These matched samples allow us to difference out a broad class of level and slope effects that might be driving our results.

To see the general form of confounding effects that our matching approach allows us to control, suppose that investments by unrelated segments and stand-alone firms are driven by the following two equations:

$$\begin{aligned} cxs_{U(j)t} &= a_U + b_{jt}(observable) \\ &\quad + [c_U + c_{jt}(observable)] * Q_{j,t-1} + d * cfs_{Ut}, \end{aligned} \tag{2}$$

$$\begin{aligned} cxs_{S(j)t} &= a_S + b_{jt}(observable) \\ &\quad + [c_S + c_{jt}(observable)] * Q_{j,t-1} + d * cfs_{St}. \end{aligned} \tag{3}$$

Taking the difference of matched pairs removes the potentially confounding effects of $b_{jt}(observable)$ and $c_{jt}(observable)$, whose functional forms are generally unknown and therefore difficult if not impossible to control directly. For example, if age and industry are the observable variables, the matching procedure will eliminate their effect on the intercept and slope terms, b_{jt} and c_{jt}:

$$\Delta cxs_{US(j)t} = \underbrace{[a_U - a_S]}_{a} + \underbrace{[c_U - c_S]}_{c} * Q_{j,t-1} + d * \Delta cfs_{US(j)t}. \tag{4}$$

In Table 3, we run this differenced specification for matched samples of unrelated segments and stand-alone firms formed on the basis of industry, year, size, and age. Matching is always exact for industry and year, and without replacement. When matching on the basis of size, we require that matched segments have sales within 10% of each other. When matching on the basis of age, we require that matched segments be in the same age category where the three broad age categories are 1–5 years, 6–10 years, and 10+ years. We

Table 3
Difference between pairs of unrelated segments and stand-alone firms: Industry, size, and age matched

	(1)	(2)	(3)
	Panel A: All industries		
Constant	0.021***	0.021***	0.014**
	[0.005]	[0.006]	[0.006]
Lagged industry Q	−0.022***	−0.019***	−0.012***
	[0.004]	[0.004]	[0.004]
Difference in cash flow/sales	0.117***	0.109***	0.138***
	[0.017]	[0.019]	[0.021]
R^2	0.029	0.024	0.036
Obs	9,176	6,001	4,282
	Panel B: Manufacturing industries		
Constant	0.013**	0.012***	0.017***
	[0.005]	[0.004]	[0.006]
Lagged industry Q	−0.017***	−0.015***	−0.018***
	[0.004]	[0.003]	[0.004]
Difference in cash flow/sales	0.091***	0.089***	0.075***
	[0.014]	[0.014]	[0.016]
R^2	0.029	0.031	0.030
Obs	6,904	4,130	2,789
	Panel C: All industries, alternative relatedness threshold (5%)		
Constant	0.035***	0.033***	0.031***
	[0.006]	[0.008]	[0.009]
Lagged industry Q	−0.030***	−0.027***	−0.026***
	[0.004]	[0.005]	[0.006]
Difference in cash flow/sales	0.060***	0.056**	0.087***
	[0.019]	[0.028]	[0.029]
R^2	0.016	0.013	0.023
Obs	4,995	3,046	2,098
	Panel D: Manufacturing industries, alternative relatedness threshold (5%)		
Constant	0.022***	0.021***	0.027***
	[0.007]	[0.005]	[0.007]
Lagged industry Q	−0.023***	−0.021***	−0.024***
	[0.005]	[0.004]	[0.006]
Difference in cash flow/sales	0.053***	0.071***	0.065***
	[0.014]	[0.016]	[0.021]
R^2	0.020	0.033	0.036
Obs	3,972	2,256	1,499

Unrelated segments are matched with stand-alone firms (Compustat segment files, 1980–2006). In column 1, unrelated segments are matched with stand-alone firms based on industry and year. In column 2, unrelated segments are matched with stand-alone firms based on industry, year, and sales. In column 3, unrelated segments are matched with stand-alone firms based on industry, year, age, and sales. Age categories are 1–5, 6–10, and 10+ years. Size matching threshold is ±10% of sales. Repeat matches are not allowed. Dependent variable is the difference in the capital spending over sales ratio of the matched pair, unrelated segment minus stand-alone firm. Industry Q in a given year is the median bounded Q of stand-alone firms in the industry. Panel B restricts the sample to manufacturing industries. Panels C and D repeat the analysis in Panels A and B, respectively, with a relatedness threshold of 5% instead of 10%. Heteroskedasticity-robust standard errors are in brackets. Standard errors are corrected for clustering at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) levels.

use three age categories due to sample size considerations. Using different size criteria to match segments (for example, assets rather than sales, matching threshold as small as 5% or as large as 20%) results in qualitatively similar results.

In column 1 of Panel A, where matching is performed on the basis of industry and year, we find a coefficient on $Q_{j,t-1}$ of −0.022, indicating that unrelated segments exhibit lower Q-sensitivity of investment than stand-alone firms. Also, the intercept is positive (0.021) and statistically significant, indicating as before that unrelated segments invest more (less) than their matched stand-alone counterparts in sufficiently low-Q (high-Q) industries. Column 2 reports results where we further match on the basis of size.[4] Both the coefficient on $Q_{j,t-1}$ (-0.019) and the intercept (0.021) are statistically significant. Finally, in column 3, we match on the basis of industry, year, age, and size. Both the coefficient on $Q_{j,t-1}$ (-0.012) and the intercept (0.014) are statistically significant. Restricting the sample to manufacturing industries in Panel B also yields similar results. Overall, the matching analysis confirms that our basic results are robust to heterogeneity in observable characteristics such as industry, size, or age.[5] In addition, we investigate the robustness of our relatedness methodology by lowering the 10% cutoff used to determine relatedness to 5%. This reduces the sample of unrelated segments by about three-fourths but yields similar results, which are reported in Panels C and D.

Recent work by Abadie and Imbens (2006), however, shows that commonly used matching procedures like ours may entail a bias term that converges at a rate slower than $N^{1/2}$. Abadie and Imbens (2007) propose a matching estimator to correct this bias, while taking account of inexact matching. We use this estimator to investigate the robustness of our results. In particular, we estimate average treatment effects, which in our context measure differences in capital spending between unrelated segments and observationally similar stand-alone firms.

Based on our prior results, we expect the average treatment effect to be positive in low-Q industries (where unrelated segments invest more than their stand-alone counterparts) and negative in high-Q industries (where unrelated segments invest less than their stand-alone counterparts). To accommodate this relation, we form two subsamples of segments with industry Q below and above the sample median industry Q in each year and estimate an average treatment effect for each subsample. We require matches to four other stand-alone firms in the sample because Abadie and Imbens (2007) find four matches to perform well in terms of mean-squared error in their simulations. We require an exact match on industry and year but allow for inexact matches on other attributes—namely, sales, age, and profitability (cash flow over sales ratio).[6]

---

[4] In the size-matched sample of column 2, unrelated segments have average sales of \$557.6 million (with a standard deviation of \$2401.3), compared with \$555.6 for stand-alone firms (with a standard deviation of \$2410.7). The difference in means is not statistically significant. We check and confirm that the matching procedure ensures that all of our matched samples have differences in means that are statistically indistinguishable from zero along the matched dimensions.

[5] Instead of taking the difference of matched pairs of unrelated segments and stand-alone firms, one could estimate pooled specifications similar to Equation (1) with matched pair fixed effects. Indeed, this alternative pooled approach is numerically equivalent to the differenced approach we report here.

[6] It is also possible, at least in principle, to match on lagged investment. The reason we do not match on lagged investment is that in our sample it is not common for segments to change their status from related to unrelated.

Table 4
Bias-corrected matching estimates

Match variables	Lagged industry Q Low	High	Difference H–L
	Panel A: All industries		
Sales, profitability	−0.0025*	−0.0086***	−0.0060***
	[0.0015]	[0.0016]	[0.0022]
Age, profitability	0.0024	−0.0034**	−0.0058***
	[0.0016]	[0.0016]	[0.0022]
Sales, age, profitability	0.0030*	−0.0031**	−0.0061***
	[0.0016]	[0.0016]	[0.0022]
	Panel B: Manufacturing industries		
Sales, profitability	−0.0034***	−0.0097***	−0.0063***
	[0.0012]	[0.0012]	[0.0017]
Age, profitability	−0.0007	−0.0058***	−0.0051***
	[0.0011]	[0.0012]	[0.0016]
Sales, age, profitability	−0.0004	−0.0054***	−0.0050***
	[0.0011]	[0.0012]	[0.0016]

Abadie and Imbens (2007) bias-corrected estimates for the average treatment effect for treated unrelated segments relative to control stand-alone firms (Compustat segment files, 1980–2006). Treatment outcome is capital spending over sales ratio. Matching is continuous with respect to sales, age, and profitability (cash flow over sales ratio) and exact with respect to industry and year. Number of matches is four. Low- and high-Q bins are based on the annual sample median of lagged industry Q. Panel B restricts the sample to manufacturing industries. Standard errors are in brackets. Comparisons between low- and high-Q bins assume independence of estimated average treatment effects. Asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) levels.

The results in this analysis are reported in two panels of Table 4. Panel A reports results based on the whole sample, whereas Panel B restricts the sample to manufacturing industries. In both panels, as predicted, we consistently find that unrelated segments in high-Q industries invest less than matched stand-alone firms—the estimates range from −0.0097 to −0.0031 depending on which set of matching variables is used and are always significant at conventional levels. In low-Q industries, we find somewhat mixed and usually insignificant treatment effects. This is not surprising in light of the fact that unrelated segments invest more than stand-alone firms only in very low-Q industries, well below the median of roughly 1.40. Indeed, when we define low-Q industries as those in the bottom quartile, we find consistently positive treatment effects (results not in table). Regardless, the difference in average treatment effects between high-Q and low-Q industries is always negative (ranging from −0.0063 to −0.0050) and statistically significant, as shown in the third column of Table 4. This is consistent with our core finding that unrelated segments are more prone to invest less than stand-alone firms in high-Q than in low-Q industries.

4. Evidence of Agency

In this section, we explore whether agency problems could explain the differences in the investment behavior of conglomerates and stand-alone firms. Our tests are motivated by the multi-tier agency model of Scharfstein and Stein (2000), which predicts that conglomerate firms will invest less than stand-alone firms in high-Q industries and more than stand-alone firms in low-Q industries. In particular, we posit that when top management of conglomerates have large ownership stakes, their firms will exhibit a greater Q-sensitivity of investment.[7] We obtain management ownership data from the ExecuComp database.

Using our previously matched samples of unrelated segments and stand-alone firms, we estimate variants of the following specification:

$$\Delta cxs_{i(j)t} = a + b * Q_{j,t-1} + c * MO_{it} + d * Q_{j,t-1} * MO_{it} + e * \Delta cfs_{it}, \quad (5)$$

where $\Delta cxs_{i(j)t}$ is the difference between the sales-normalized capital spending of unrelated segment i (operating in industry j) in year t and that of its matched stand-alone counterpart, $Q_{j,t-1}$ is the median bounded Tobin's Q of stand-alone firms in industry j in year $t-1$, MO_{it} is management ownership by top officers of the conglomerate firm that owns unrelated segment i, and $\Delta cfs_{i(j)t}$ is the difference between the sales-normalized cash flow of unrelated segment i in year t and that of its matched stand-alone counterpart. As before, our differencing approach removes potentially confounding level and slope effects.

Columns 1–3 of Table 5 report results for the industry–year-, industry–year–size-, and industry–year–age–size-matched samples, respectively. Panel A uses the whole sample, whereas Panel B restricts the analysis to manufacturing industries. Overall, the results lend strong support to agency-based explanations for the observed investment behavior of conglomerate firms in their unrelated segments. Consistent with our earlier findings, the unrelated segments of conglomerate firms exhibit lower Q-sensitivity of investment than stand-alone firms, as evidenced by statistically significant negative coefficients on $Q_{j,t-1}$. The statistically significant positive intercept terms indicate that unrelated segments in sufficiently low-Q (high-Q) industries invest more (less) than stand-alone firms. More important, Table 5 demonstrates that, consistent with the agency view, unrelated segments of conglomerate firms with high management ownership appear to suffer less from this allocative inefficiency, as evidenced by statistically significant positive coefficients on the interaction term $Q_{j,t-1} * MO_{it}$ and negative coefficients on MO_{it}. The only exception is column 2 in Panel B, where the coefficients of interest have the predicted signs but lack statistical significance.

The coefficient estimates in Panel A, however, imply unrealistically high levels of management ownership at which a conglomerate firm would have the same Q-sensitivity of investment and roughly the same level of investment as a stand-alone firm. For example, in Panel A, column 3, management ownership as high as 16.5% (about the 85th percentile in the distribution of management ownership) would erase the negative coefficient on $Q_{j,t-1}$ (−0.040) given

[7] Note that several other theoretical models also predict inefficient allocation of capital in internal capital markets, but they build on agency problems lower down in the organization for which we have no data. For models that involve strategic interaction among multiple managers, see Rajan, Servaes, and Zingales (2000) and Ozbas (2005). For models that analyze a single manager in isolation, see Harris and Raviv (1996); Bernardo, Cai, and Luo (2001); and Marino and Matsusaka (2005).

Table 5
Evidence on agency: Difference between matched pairs of unrelated segments and stand-alone firms

	(1)	(2)	(3)
Panel A: All industries			
Constant	0.045***	0.070***	0.059***
	[0.010]	[0.018]	[0.020]
Lagged industry Q	−0.035***	−0.050***	−0.040***
	[0.006]	[0.011]	[0.011]
Management ownership	−0.220**	−0.296**	−0.349**
	[0.096]	[0.141]	[0.170]
Lagged industry Q × Management ownership	0.142**	0.197**	0.243**
	[0.059]	[0.091]	[0.108]
Difference in cash flow/sales	0.094***	0.128***	0.124**
	[0.031]	[0.044]	[0.054]
R^2	0.031	0.049	0.040
Obs	2,349	1,495	1,211
Panel B: Manufacturing industries			
Constant	0.020**	0.015	0.025**
	[0.008]	[0.010]	[0.012]
Lagged industry Q	−0.022***	−0.017**	−0.022***
	[0.005]	[0.007]	[0.008]
Management ownership	−0.163**	−0.163	−0.429*
	[0.079]	[0.165]	[0.237]
Lagged industry Q × Management ownership	0.109**	0.110	0.278*
	[0.051]	[0.109]	[0.160]
Difference in cash flow/sales	0.070***	0.149***	0.112***
	[0.027]	[0.027]	[0.033]
R^2	0.023	0.092	0.076
Obs	1,681	1,012	764

Unrelated segments are matched with stand-alone firms (Compustat segment files, 1980–2006). The matching procedure is described in Table 3. Dependent variable is the difference in the capital spending over sales ratio of the matched pair, unrelated segment minus stand-alone firm. (Using Standard & Poor's ExecuComp database) Management Ownership is defined as the sum of stocks and options held by top officers as a fraction of outstanding shares. Panel B restricts the sample to manufacturing industries. Heteroskedasticity-robust standard errors are in brackets. Standard errors are corrected for clustering at the industry-year level. Asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) levels.

the positive coefficient on the interaction term $Q_{j,t-1} * MO_{it}$ (0.243) and at the same time almost offset the level effect in the intercept (0.059) given the negative coefficient on MO_{it} (−0.349). By comparison, the results in Panel B for manufacturing industries indicate that lower levels of management ownership (about 7.9% in column 3—about the 75th percentile in the distribution of management ownership) would achieve similar effects.

Finally, we check the robustness of our results about managerial ownership using the bias-corrected matching estimator of Abadie and Imbens (2007). The same rationale for estimating average treatment effects separately for low-Q and high-Q industries applies here as well. In addition, because our results suggest that the treatment effect is different depending on the level of managerial ownership, we estimate average treatment effects separately for low- and high-managerial ownership subsamples comprising observations with managerial ownership below and above the sample median in each year. As before, we require four exact matches on industry and year. In addition, we add managerial ownership to the set of continuously matched covariates—namely, sales, age,

Table 6
Evidence on agency: Bias-corrected matching estimates

Management ownership	Lagged industry Q: Low	Lagged industry Q: High	Difference H–L
	Panel A: All industries		
All	0.0146**	−0.0085**	−0.0231***
	[0.0061]	[0.0035]	[0.0070]
Low	0.0222***	−0.0130***	−0.0352***
	[0.0084]	[0.0038]	[0.0092]
High	0.0021	−0.0050	−0.0071
	[0.0100]	[0.0076]	[0.0126]
	Panel B: Manufacturing industries		
All	0.0050	−0.0159***	−0.0209***
	[0.0046]	[0.0057]	[0.0073]
Low	0.0090*	−0.0221***	−0.0311***
	[0.0049]	[0.0063]	[0.0079]
High	−0.0046	−0.0035	0.0011
	[0.0090]	[0.0115]	[0.0146]

Abadie and Imbens (2007) bias-corrected estimates for the average treatment effect for treated unrelated segments relative to control stand-alone firms (Compustat segment files, 1980–2006). Treatment outcome is capital spending over sales ratio. Matching is continuous with respect to sales, age, management ownership, and profitability (cash flow over sales ratio) and exact with respect to industry and year. Number of matches is four. Low- and high-Q bins are based on the annual sample median of lagged industry Q. Low- and high-management ownership bins are based on the annual sample median of management ownership. Panel B restricts the sample to manufacturing industries. Standard errors are in brackets. Comparisons between different bins assume independence of estimated average treatment effects. Asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) levels.

and profitability (cash flow over sales ratio)—to address a potential concern that managerial ownership may proxy for unobserved firm characteristics that change the Q-sensitivity of investment (rather than treatment).

Table 6 presents our results in two panels. Panel A uses the whole sample, and Panel B restricts the sample to manufacturing industries. In both panels, we continue to find that unrelated segments in high-Q industries invest less (−0.0085 in Panel A and −0.0159 in Panel B) than matched stand-alone firms. This is similar to Table 4 except that managerial ownership is added to the set of continuously matched covariates. Consistent with the agency explanation, the effect appears to be strong especially when managerial ownership is low (−0.0130 in Panel A and −0.0221 in Panel B) and disappears when managerial ownership is high. We find some evidence that unrelated segments in low-Q industries invest more than matched stand-alone firms when not conditioning on managerial ownership (statistically significant in Panel A, but not in Panel B). Strikingly, the results strengthen when managerial ownership is low (0.0222 in Panel A and 0.0090 in Panel B, both significant at conventional levels) and disappear when managerial ownership is high. Also, the difference between high-Q and low-Q industries is always significantly negative when not conditioning on managerial ownership (−0.0231 in Panel A and −0.0209 in Panel B). The relation strengthens when managerial ownership is low (−0.0352 in Panel A and −0.0311 in Panel B) and disappears when managerial ownership is high, consistent with the agency explanation.

In interpreting these results, it is important to keep in mind that we do not have exogenous variation in managerial ownership. It is possible that managerial ownership proxies for another factor that affects investment. One concern is that an unrelated segment of a high-managerial ownership firm may be large relative to the overall firm. In this case, there would be less scope for cross-subsidization in an internal capital market. As a result, the investment of unrelated segments of high-managerial ownership firms would appear to be more similar to stand-alone firms. However, we find that unrelated segments of high-managerial ownership firms account for 38% of firm sales, while unrelated segments of low-managerial ownership firms account for 35% of firm sales. The difference is small and therefore unlikely to explain our findings. Of course, it is possible that managerial ownership proxies for other factors that are themselves related to the difference in the investment of unrelated segments and stand-alone firms (after matching on size, age, industry, and profitability), but it is not apparent to us what these factors might be.

5. Conclusion

This article presents evidence of inefficiencies in internal capital markets. The investment of stand-alone firms is more sensitive to industry Q than the investment of unrelated segments of conglomerate firms. In addition, the unrelated segments of conglomerate firms tend to invest less than stand-alone firms in high-Q industries, and more than stand-alone firms in low-Q industries. These findings are robust to industry, size, and age matching. In addition, these findings are more pronounced in conglomerate firms in which managers have small ownership stakes, suggesting that the inefficient investment behavior of conglomerate firms is, at least in part, due to agency problems at the top of conglomerates.

There are a number of directions in which one can take the research question of this article. First, our findings point to inefficiencies in corporate resource allocation, but they do not provide nearly the full account that one would like. For example, our findings are consistent with there being agency problems among top managers. But theoretically, this is not sufficient to generate inefficient resource allocation. A good example of this is Stein (1997). In his model, external capital markets ration resources to a CEO who is prone to overinvest. But because the CEO prefers managing a more profitable empire over a less profitable empire, resources flow from divisions with poor investment opportunities to divisions with good investment opportunities.

Stein's model is a useful benchmark in that it shows that agency problems lower down in the organization are necessary to generate inefficient resource allocation. Thus, one would like to know more about the nature of the agency problem lower down in the organization as well as the kinds of organizational processes and structure that firms use to mitigate agency problems within. Manager promotion and rotation policies across divisions may be one way to mitigate divisional incentives for overinvestment (Xuan 2006), as would more high-powered incentives for divisional managers (Palia and Ye 2003). The formal and informal rules companies use to make capital allocation decisions are also likely to have an important impact on investment behavior (Bower 1970; Ozbas 2005; Stein 2002).

Second, our focus here has been on analyzing the effect of internal capital markets on capital investment. Yet, there are many other types of investments that firms undertake, such as research and development, marketing, and certain pricing policies. Analyzing these decisions in the context of internal capital allocation is also an important avenue for future research.

Finally, papers such as Berger et al. (2005), Guedj and Scharfstein (2005), Khanna and Tice (2001), and Mullainathan and Scharfstein (2001) have shown the benefit of analyzing rich industry-specific data sets and also of having a specific industry context in which to interpret the results. More industry-focused work along these lines would be useful in identifying the costs and benefits of internal capital markets.

Appendix: Relatedness Measure

The standard two-digit SIC approach is somewhat limited when it comes to identifying vertical relationships because the SIC numbering system is organized horizontally. For example, drilling oil wells and other exploration services have the same two-digit SIC code, but the next vertical stage of petroleum refining does not. To establish vertical relationships that the two-digit SIC approach seems to miss, we use the Input-Output Benchmark Surveys conducted by the Bureau of Economic Analysis.

The Use Table of the Input-Output Benchmark Surveys is our main data source for identifying significant vertical relationships that are not captured by the two-digit SIC approach. Essentially, the Use Table is a matrix that contains the dollar value of commodity flows measured in producers' prices between what are called the Input-Output Accounts of the US economy. These I-O accounts are defined by the survey and represent industries that are significant enough to be classified as a separate account. While the number and definition of I-O accounts change from survey to survey, a table that lists I-O account numbers, titles, and associated SIC or NAICS codes is provided in each survey.

We identify significant vertical relationships first by looking at the Use Table from the perspective of a purchasing industry. We calculate use coefficients by dividing the purchases of an industry by its total purchases and keep the I-O pairs with use coefficients above 10%, which is the cutoff used by Matsusaka (1993). We then look at the Use Table from the perspective of a selling industry. Similar to use coefficients, we calculate make coefficients by dividing the sales of an industry by its total sales and keep the I-O pairs with make coefficients above 10%.

The Bureau of Economic Analysis publishes a new Input-Output Benchmark Survey roughly once every five years to coincide with the Economic Census conducted by the US Census Bureau, and we draw on six different surveys (2002, 1997, 1992, 1987, 1982, and 1977) on a rolling basis to identify vertical relationships. We adopt this approach primarily to improve measurement accuracy because each survey provides a historical snapshot and thus may be inadequate for describing the structure of the US economy for our entire sample period from 1979 to 2006. We use data from a given survey until a new snapshot is provided by the following survey. Specifically, we rely on 1977 data between 1977 and 1981, 1982 data between 1982 and 1986, and so on.

When calculating use and make coefficients, we exclude I-O accounts greater than 77 (1992, 1987, 1982, 1977) or labeled S (2002, 1997). These are mainly government accounts without an associated SIC or NAICS code. Also excluded are accounts that are related to inventory adjustments, employee compensation, and industry value-added. These accounts have nothing to do with the vertical relationships we are trying to identify. Including them would introduce an unnecessary source of measurement error.

References

Abadie, A., and G. Imbens. 2006. Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica* 74:235–67.

Abadie, A., and G. Imbens. 2007. Bias Corrected Matching Estimators for Average Treatment Effects. Working Paper, Harvard University and NBER.

Baker, M., J. Stein, and J. Wurgler. 2003. When Does the Market Matter? Stock Prices and the Investment of Equity Dependent Firms. *Quarterly Journal of Economics* 118:969–1006.

Berger, A., N. Miller, M. Petersen, R. Rajan, and J. Stein. 2005. Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks. *Journal of Financial Economics* 76:237–69.

Bernardo, A., H. Cai, and J. Luo. 2001. Capital Budgeting and Compensation with Asymmetric Information and Moral Hazard. *Journal of Financial Economics* 61:311–44.

Billett, M., and D. Mauer. 2003. Cross-Subsidies, External Financing Constraints, and the Contribution of the Internal Capital Market to Firm Value. *Review of Financial Studies* 16:1167–201.

Bower, J. 1970. *Managing the Resource Allocation Process*. Cambridge, MA: Harvard Business School Press.

Eccles, R. 1985. Transfer Pricing as a Problem of Agency. In John W. Pratt and Richard J. Zeckhauser (eds.), *Principals and Agents: The Structure of Business,* pp. 151–86. Boston, MA: Harvard Business School Press.

Fan, J., and L. Lang. 2000. The Measurement of Relatedness: An Application to Corporate Diversification. *Journal of Business* 73:629–60.

Gertner, R., E. Powers, and D. Scharfstein. 2002. Learning about Internal Capital Markets from Corporate Spinoffs. *Journal of Finance* 57:2479–506.

Gertner, R., D. Scharfstein, and J. Stein. 1994. Internal Versus External Capital Markets. *Quarterly Journal of Economics* 109:1211–30.

Guedj, I., and D. Scharfstein. 2005. Organizational Scope and Investment: Evidence from the Drug Development Strategies and Performance of Biopharmaceutical Firms. Working Paper, Harvard University and NBER.

Harris, M., and A. Raviv. 1996. The Capital Budgeting Process: Incentives and Information. *Journal of Finance* 51:1139–74.

Kaplan, S., and L. Zingales. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics* 112:169–215.

Khanna, N., and S. Tice. 2001. The Bright Side of Internal Capital Markets. *Journal of Finance* 56:1489–528.

Lamont, O. 1997. Cash Flow and Investment: Evidence from Internal Capital Markets. *Journal of Finance* 52:83–109.

Marino, A., and J. Matsusaka. 2005. Decision Processes, Agency Problems, and Information: An Economic Analysis of Budget Procedures. *Review of Financial Studies* 18:301–25.

Matsusaka, J. 1993. Takeover Motives during the Conglomerate Merger Wave. *RAND Journal of Economics* 24:357–79.

Meyer, M., P. Milgrom, and J. Roberts. 1992. Organizational Prospects, Influence Costs and Ownership Changes. *Journal of Economics and Management Strategy* 1:9–35.

Mullainathan, S., and D. Scharfstein. 2001. Do Firm Boundaries Matter? *American Economic Review Papers and Proceedings* 91:195–99.

Ozbas, O. 2005. Integration, Organizational Processes and Allocation of Resources. *Journal of Financial Economics* 75:201–42.

Palia, D., and J. Ye. 2003. Diversification and Managerial Compensation. Working Paper, Rutgers University.

Perfect, S., and K. Wiles. 1994. Alternative Constructions of Tobin's q: An Empirical Comparison. *Journal of Empirical Finance* 1:313–41.

Rajan, R., H. Servaes, and L. Zingales. 2000. The Cost of Diversity: The Diversification Discount and Inefficient Investment. *Journal of Finance* 55:35–80.

Scharfstein, D., and J. Stein. 2000. The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment. *Journal of Finance* 55:2537–64.

Shin, H., and R. Stulz. 1998. Are Internal Capital Markets Efficient? *Quarterly Journal of Economics* 113:531–52.

Stein, J. 1997. Internal Capital Markets and the Competition for Corporate Resources. *Journal of Finance* 52:111–33.

Stein, J. 2002. Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *Journal of Finance* 57:1891–921.

Williamson, O. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications*. New York, NY: Free Press.

Xuan, Y. 2006. Empire-Building or Bridge-Building? Evidence from New CEOs' Internal Capital Allocation Decisions. Working Paper, Harvard Business School.