Dissecting Conglomerates

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April 6, 2016

ABSTRACT

We develop a method to calculate valuation multiples of conglomerate divisions that does not rely on standalone firms. These valuations differ considerably from commonly used industry multiples, and range across industries from deep discounts to large premiums relative to standalone firms. Contrary to prior studies, conglomerate investment is highly sensitive to investment opportunities as measured by division multiples. Consistent with theory, non-core divisions and those in weak or capital-intensive industries have higher valuations, whereas divisions in innovative or competitive industries have lower valuations. Overall, we provide first estimates of intra-conglomerate multiples that shed new light on conglomerate investment and value.

JEL Classification: G32, G34.

Keywords: boundaries of the firm, segment valuation, conglomerate investment, internal capital markets, quantile regressions.

*We thank Tom Bates, Cláudia Custódio, John Matsusaka, Jan Mahrt-Smith, Igor Salitskiy and seminar participants at Arizona State University, Nova School of Business and Economics, the University of Rochester, York University, and the European Winter Finance Summit for helpful comments. Boguth: W. P. Carey School of Business, Arizona State University, PO Box 873906, Tempe, AZ 85287-3906. Duchin: Foster School of Business, University of Washington, PO Box 353226, Seattle, WA 98195-3226. Simutin: Rotman School of Management, University of Toronto, 105 St. George Street, Toronto ON, Canada, M5S 3E6.

What is the relation between corporate diversification and firm value? This question has been at the forefront of contemporary research in corporate finance. Early studies show convincingly that conglomerates trade at a discount relative to a mimicking portfolio of standalone firms (e.g., Lang and Stulz (1994), Berger and Ofek (1995), Servaes (1996), Lins and Servaes (1999), and Denis, Denis, and Yost (2002)). However, subsequent studies argue that self-selection and data limitations can explain this discount (e.g., Campa and Kedia (2002), Graham, Lemmon, and Wolf (2002), Lamont and Polk (2002), and Villalonga (2003, 2004a,b)). Despite this voluminous literature on conglomerate value, we still know relatively little about the value of the individual divisions that make up the conglomerate firm.

In this paper, we provide this evidence by developing a novel method to estimate valuation multiples of conglomerate divisions. The traditional empirical approach to studying conglomerate value, which was pioneered by Lang and Stulz (1994) and Berger and Ofek (1995), synthetically replicates the overall conglomerate by a portfolio of standalone firms. Specifically, this approach imputes the vector of valuations of diversified firms as $\hat{v} = W \cdot q^{\text{SA}}$, where W is a matrix of firms' industry exposures of fundamentals (e.g., sales), and q^{SA} is a vector of industry multiples derived from standalone firms. It then compares $\hat{v}$ to the actual value v to obtain conglomerates' excess values, $\text{EV} = \log(v/\hat{v})$. This approach has two important limitations. First, it does not provide disaggregated information on within-conglomerate valuations. Second, it assumes that industry valuations of standalone firms reflect division valuations, despite potentially unobservable differences between conglomerate divisions and standalone firms.

To address these limitations, rather than valuing conglomerates relative to a portfolio of standalone firms, we form portfolios of conglomerates to mimic standalone firms. Specifically, we use data on v and W to directly estimate a vector of conglomerate-implied industry valuation multiples $\hat{q}^{\text{C}}$. We then compare $\hat{q}^{\text{C}}$ to the vector of standalone valuation multiples q^{SA} to derive relative division valuations, $\text{RDV} = \log(\hat{q}^{\text{C}}/q^{\text{SA}})$.

As a simple example, consider two conglomerates that operate in the same two industries. The first conglomerate has unit exposure of fundamentals to each industry, and the second conglomerate has exposures of two and one to these two industries, respectively. It is immediately clear that a portfolio long the second conglomerate and short the first conglomerate has exposures of one and zero to the two industries. The value of the portfolio is the conglomerate-implied valuation of divisions operating in the first industry.

In this example, the solution to the problem is unique and can be obtained by inverting the matrix containing the proportions of conglomerate exposure to each industry. For practical applications, the number of conglomerates exceeds the number of industries, and this matrix is not invertible. We show in Monte-Carlo simulations that median regressions of conglomerate valuation multiplies on the matrix of exposure weights provide reliable estimates of the valuation multiples of conglomerate divisions.

We apply our method to provide three main analyses. First, we study conglomerate valuations across industries and compare them to the commonly used industry valuations derived from standalone firms. Second, we investigate conglomerate investment decisions and internal capital allocation. Third, we study the determinants of intra-conglomerate values proposed by corporate diversification theory.

We begin by investigating division valuations across industries. A benefit of our approach is that it allows us to study within-conglomerate, across-industry variation in valuation multiples, which cannot be inferred from standard measures of excess value. This cross-industry variation is important for understanding corporate diversification. As noted by Maksimovic and Phillips (2007) and implied by Coase (1937), corporate diversification matters only if the conglomerate's industry composition has an effect on its costs of transacting and consequently its optimal boundaries. As Lang and Stulz (1994) conclude, "a more detailed disaggregated analysis of the benefits and costs of diversification would be useful" (p. 1279).

Our industry analysis produces two key findings. First, it reveals large differences between division valuations and industry valuations of standalone firms. These differences suggest that empirical proxies based on industry multiples of standalone firms mis-measure the valuation multiples inside conglomerates.

Second, our findings show considerable variation in average valuations of divisions relative to standalone firms across industries. Relative division valuations (RDVs) range from a discount of -56% to a premium of 19%. RDVs are lowest in the energy, high-tech, and healthcare industries, whereas divisions in the consumer nondurables and telecommunication industries trade at substantial premiums relative to standalone firms. This rich variation in RDVs is uncaptured by the negative aggregate estimates of conglomerate excess value. It indicates that the value of conglomeration varies systematically across industries, implying that industry composition is a key determinant of conglomerate value.

These findings have broad implications for prior research on corporate diversification. First, theories of cross-subsidization of weak divisions (e.g., Rajan, Servaes, and Zingales (2000), Scharfstein and Stein (2000)) and explanations based on the endogenous decision to diversify through acquisitions (e.g., Graham, Lemmon, and Wolf (2002), Campa and Kedia (2002)) would require systematic differences across industries.

Second, industry-specific analyses should be interpreted cautiously. For example, Maksimovic and Phillips (2002) and Schoar (2002) use the Longitudinal Research Database to investigate value and productivity of conglomerate divisions. However, this database tracks only manufacturing plants, a limitation the authors acknowledge. Consistent with these studies, our estimates also show that divisions in the manufacturing sector are not significantly discounted. However, this conclusion does not extrapolate to other industries, where we find both deep discounts and substantial premiums.[1]

One caveat with the above analysis is that the value of operating an industry inside a conglomerate could be affected by the other divisions. In particular, the industry composition of a conglomerate is not random. For example, Hoberg and Phillips (2015)

[1]Other examples of studies that focus on a single industry include Lamont (1997), who studies investment decisions of diversified oil companies following the oil price shock of 1986; Khanna and Tice (2001), who study the responses of diversified firms to Wal-Mart's entry into their market; Campello (2002), who analyzes the reactions of financial conglomerates to monetary policy; and Guedj and Scharfstein (2004), who analyze the development strategies and performance of biopharmaceutical firms.

show that conglomerates tend to operate in economically related industries. Such endogenous matching can affect division valuations.

To assess this possibility, we investigate within-conglomerate industry pairs. Consistent with nonrandom industry matching, we find that industry pairs are not equally distributed. For example, 69% of conglomerates operating a division in consumer durables also operate a division in manufacturing, compared to 12% of coglomerates with a division in telecommunications and 15% of coglomerates with a division in utilities.

More importantly, we find an insignificant relation between the average valuation of divisions and their pairing with other industries inside the conglomerate. Across all industries, the exclusion of industry pairs does not have a sizeable effect on the average RDV. In particular, RDVs estimated after excluding industry pairs are statistically different from the full-sample RDVs at the 5% level only in 6.7% of cases. Overall, this evidence suggests that the cross-industry variation in RDVs continues to hold after accounting for endogenous conglomerate-industry matching.

In our second set of analyses, we investigate conglomerate investment following Shin and Stulz (1998) and Ozbas and Scharfstein (2010). These studies use the neoclassical relation between investment and Tobin's q to study the efficacy of conglomerates' internal capital allocation. Using estimates of investment opportunities derived from qs of standalone firms, they find that investment in conglomerate divisions is less sensitive to investment opportunities than in standalone firms. These results are broadly interpreted as evidence that conglomerate divisions overinvest when opportunities are low and underinvest when they are high.

One concern with these studies is their use of standalone firms to measure Tobin's q at the conglomerate-division level. Whited (2001) and Maksimovic and Phillips (2002) demonstrate that estimates of investment opportunities derived from qs of standalone firms are inappropriate for the study of investment by conglomerate divisions because of measurement errors that may arise due to unobservable differences between conglomerate divisions and standalone firms.

In contrast, our method generates division-level estimates of valuation multiples that are not reliant on standalone benchmarks. Therefore, these estimates are largely free from the above measurement errors. We use these estimates to revisit the relation between Tobin's q and conglomerate investment.

Our results are striking. Divisional investment is not sensitive to Tobin's qs estimated from standalone firms. It is highly sensitive, however, to our conglomerate-implied qs. Conversely, investment in standalone firms is only sensitive to qs of standalone firms. These findings are less consistent with the hypothesis that conglomerates invest inefficiently, and instead lend support to the aforementioned critique that qs of conglomerate divisions and stand-alone firms are different. Overall, the findings suggest that our method generates clean measures of investment opportunities at conglomerate divisions.

Our third set of analyses seeks to shed light on the economic mechanisms related to conglomerate value by identifying the types of divisions that conglomerate firms run most or least efficiently compared to standalone firms. We consider two conflicting hypotheses. The first, which we label the *bright side view*, posits that the internal capital markets in conglomerate firms allow to raise more external finance (Lewellen (1971), Hadlock, Ryngaert, and Thomas (2001)) and allocate capital more efficiently (Alchian (1969), Weston (1970), Stein (1997), and Matsusaka and Nanda (2002)). This hypothesis implies that conglomerate divisions invest more efficiently and have higher valuations relative to standalone firms.

The second hypothesis, which we label the *dark side view*, suggests that conglomerate firms suffer from agency problems and, in particular, from the rent-seeking behavior of divisional managers. According to this view, the CEO tilts the conglomerate's internal capital budget toward weaker divisions to retain divisional managers (Scharfstein and Stein, 2000) and to control their rent-seeking behavior (Rajan, Servaes, and Zingales, 2000). This hypothesis implies that conglomerate divisions invest less efficiently and have lower valuations relative to standalone firms.

We study the bright side view by investigating the impact of industry conditions on RDVs. We find that RDVs in weak industries exceed those in strong industries by 19%. Furthermore, we show that the higher relative valuations of divisions operating in weak industries more than offset the lower valuations of divisions operating in strong industries. This evidence supports the bright side hypothesis and suggests that one advantage of conglomeration lies in its resilience when facing adverse economic shocks. In particular, conglomerates can capture rents in weak industries by reallocating internal resources unavailable to standalone firms.

Lending further support to the bright side view, we find that divisions operating in capital-intensive industries have higher RDVs. In particular, divisions in low capital intensity industries trade at a discount of 29% relative to their standalone peers, whereas those in high capital intensity industries trade at a premium of 11%. This result suggests that access to internal capital markets is associated with a higher value of conglomeration.

We investigate the dark side view by studying the link between the valuation of conglomerate divisions and the levels of innovation and product market competition in their industry. Our cross-industry analysis suggests that RDVs are lower in innovation-intensive industries such as high-tech and healthcare, and higher in low-innovation industries such as consumer nondurables. We further test this link by considering direct measures of innovation including research and development (R&D) intensity and patent intensity. We find that RDVs are lower in industries characterized by high levels of R&D and patent intensity. These findings are consistent with the evidence in Seru (2014), who shows that firms acquired in diversifying acquisitions are less innovative.

We also find that conglomerate divisions are more discounted relative to standalone firms in competitive industries. These results are economically large and hold across different measures of product market competition. For example, based on the Herfindahl index, RDVs in concentrated industries exceed those in competitive industries by 32%. To investigate the origins of this effect, we use exogenous increases in competition following industry deregulation. Our difference-in-differences estimates indicate that the value of conglomerate divisions relative to standalone firms declines significantly following industry deregulation.

These findings are consistent with the predictions of Matsusaka and Nanda (2002), who show that the flexibility available to the conglomerate headquarters creates a strategic disadvantage in product market competition. A rival firm will not enter a market if it believes the incumbent firm will be investing heavily. Conglomerates, however, cannot commit credibly to such investment.

Finally, we investigate the value-implications of a firm's endogenous decision to diversify. Prior studies such as Campa and Kedia (2002), Villalonga (2004b), and Graham, Lemmon, and Wolf (2002) show that after controlling for this selection effect, conglomerates no longer appear discounted. Consistent with these findings, Matsusaka (2001) develops a dynamic search model in which diversification is an optimal search process by which firms seek to acquire businesses that are good matches for their capabilities. In his model, diversified firms are discounted because they choose to diversify when their value decreases and not because they make bad diversification decisions.

Our findings are consistent with these predictions. We find that conglomerates' core divisions are valued at significantly higher discounts (-23%) than are peripheral divisions (-11%). These results suggest that lower conglomerate values do not arise solely from diversifying into low-valuation peripheral divisions. Instead, discounted firms are those that choose to diversify.

Overall, our paper contributes to the literature on corporate diversification and internal capital markets. It makes a step towards a better understanding of the investment decisions and value drivers in diversified firms by providing clean disaggregated estimates of division-level valuation multiples.

I. Conglomerate-Implied Valuation Multiples

Our analysis inverts the traditional approach of Lang and Stulz (1994) and Berger and Ofek (1995). Rather than building up synthetic conglomerates from individual pieces (standalone firms), we break down actual conglomerates into components. We group these components across conglomerates into "classes" that share observable characteristics, such as industry association or other division attributes. We then use median regressions to obtain conglomerate-implied valuation ratios for each class. Comparing these synthetic valuations with valuations of actual standalone firms in each class allows us to analyze conglomerates at the granular level of a single class.

A. Overview of Estimation Method

Let W denote the I conglomerates by K classes matrix that contains the fundamentals (e.g., sales) of a cross-section of conglomerates. For example, in the analysis of Berger and Ofek (1995), K represents the number of 4-digit SIC industries in which the I conglomerates operate. If divisions in all classes function independently, the value of the conglomerate, v, should equal the sum of class values,

$$v = W \cdot q^{\mathrm{C}}, \tag{1}$$

where q^{C} is a $K \times 1$ vector containing the valuation ratios of the classes. In the special case where W contains the replacement costs of capital, q^{C} corresponds to Tobin's q. Because replacement costs are not observable, the corporate diversification literature relies on asset or sales multiples to proxy for Tobin's q (Lang and Stulz, 1994).

The traditional approach of Lang and Stulz (1994) and Berger and Ofek (1995) imputes the value of conglomerates using industry-level multiples estimated from standalone firms. In particular, they estimate valuation ratios of each division as the median of the valuation ratios of standalone firms operating in the same industry, $\hat{q}^{\mathrm{C}} = q^{\mathrm{SA}}$. The imputed values of conglomerates, $\hat{v} = W \cdot q^{\mathrm{SA}}$, exceed their market capitalization on average, suggesting that diversified firms are valued at a discount.

We also build on Equation (1), but we aim to estimate q^{C} using only conglomerate-level information. In particular, we scale Equation (1) by the total fundamentals of each conglomerate to obtain

$$\tilde{v} = \tilde{W} \cdot q^{\mathrm{C}}, \tag{2}$$

where $\tilde{v}(i) = v(i)/\sum_k W(i,k)$ and $\tilde{W}(i,k) = W(i,k)/\sum_k W(i,k)$ are valuation multiples and class weights of the conglomerates.

Ostensibly, estimating $\hat{q}^{\mathrm{C}}$ from Equation (2) could be achieved via an ordinary least squares (OLS) regression of conglomerate multiples on class weights. However, the OLS approach is problematic since valuation ratios are positively skewed. The prior literature addresses the skewness in valuation ratios by taking their natural logarithms, an approach not suitable for our purposes since logs are not additive. To resolve the problem of skewed valuation ratios, we base our analysis on medians rather than means, and use quantile regressions. Specifically, we use median regressions of conglomerate multiples $\tilde{v}$ on class weights $\tilde{W}$ to back out the class valuation ratios $\hat{q}^{\mathrm{C}}$.

B. Median Regressions

Before describing our analysis in detail, we provide a short review of quantile regressions. Our goal is to fit the median of the target variable y_i conditional on the explanatory variables X_i. When estimating Equation (2), y_i corresponds to the valuation ratio of conglomerate i, $\tilde{v}(i)$, and X_i is the ith row of the weight matrix $\tilde{W}$. The median, or 50th percentile, of y_i is defined from its inverse probability distribution function

$$P^{50}(y_i) = \inf\left\{y : Prob\left(y_i < y\right) \geq 0.50\right\}. \tag{3}$$

We can express the median as the solution to an optimization problem

$$P^{50}(y_i) = \arg\inf_u \mathbb{E}\left|y_i - u\right|, \tag{4}$$

which is particularly convenient for handling conditioning information sets such as the explanatory variables.[2] We follow the seminal quantile regression specification of

[2]Equation (4) is a special case of the general quantile regression representation, where the *quantile loss function* for quantile τ is given by $\rho_\tau(x) = x\left(\tau - \mathbb{I}_{(x<0)}\right)$ and the optimization problem is $P^\tau(y_i) = \arg\inf_u \mathbb{E}\left[\rho_\tau\left(y_i - u\right)\right]$.

Koenker and Bassett (1978), and assume that the median of y_i conditional on X_i is a linear function of the explanatory variables. This implies

$$P^{50}\left(y_i \middle| X_i\right) = \arg\inf_u \mathbb{E}\left(|y_i - u| \middle| X_i\right) = \gamma_0 + \gamma_1 X_i. \tag{5}$$

The assumed linear relation is reminiscent of standard OLS specifications. However, median regressions model the conditional median of y_i, rather than its mean, as a linear function of X_i.

C. Simulation

We use Monte Carlo simulations to show that valuation ratios of division classes can be robustly estimated using median regressions rather than OLS regressions if conglomerate valuation ratios are positively skewed (e.g., Berger and Ofek, 1995). For $I = 500$ conglomerates, we simulate fundamentals across $K = 5$ classes. Half of the conglomerates operate in two classes, a third in three classes, and a sixth in four classes, approximately in line with the empirical distribution. Fundamentals W are drawn from a lognormal distribution that is based on a Gaussian distribution with unit mean and a standard deviation of 0.8.[3]

The valuation ratios of conglomerates, $\tilde{v}$, are calculated as in Equation (2), where the class valuations are given by $q^{\mathrm{C}} = [0.5\ 1.0\ 1.5\ 2.0\ 2.5]'$, and exposed to a multiplicative valuation shock. The shock has a median of one, and is drawn from either a Gaussian distribution that is truncated at zero or a lognormal distribution. It reflects the significant empirical variation in excess values. For example, Lamont and Polk (2001) report cross-sectional standard deviations of excess value between 0.36 and 0.63, depending on whether valuation ratios are based on asset or sales multiples. Correspondingly, we consider two standard deviations for our shock, 0.3 and 0.6.

Table I shows the average and standard deviation across 100,000 simulations of the difference between the estimated and actual class valuations, $\hat{q}^{\mathrm{C}} - q^{\mathrm{C}}$. In the last

[3]This standard deviation implies that, on average, conglomerates are well diversified and not dominated by an individual division class. The average Herfindahl index across conglomerates is about 0.5. It ranges from 0.35 for four-division firms to 0.6 for two-division firms, closely matching the empirical moments we obtain in untabulated analysis.

column, it also shows excess value measures computed as in Berger and Ofek (1995). In Panel A, we assume a modest cross-sectional variation in excess values of 0.3. It shows that when conglomerate valuation ratios are normally distributed, both median regressions and OLS regressions yield unbiased estimates of class valuations. The cross-simulation average of the median excess value is zero, but that of its mean is slightly negative (-0.05). The use of the logarithm in the excess value calculation directly aims to eliminate the effects of positive skewness. Without positive skewness, Jensen's inequality implies a downward-biased measure.

Several observations about the cross-simulation standard deviations, shown in parentheses, are noteworthy. First, they are increasing across the five classes. This is simply an artifact of having increasing valuation ratios across the classes, and a multiplicative valuation shock. Second, as expected with normally distributed residuals, OLS is more efficient than median regressions. Last, the standard deviations of class valuations are significantly higher than the standard deviation of the excess values. This is not surprising given that the same data are used to obtain one estimate of excess value and five estimates of class valuation multiples. A finer granularity comes at a cost of reduced efficiency.

The OLS-based inferences change dramatically when valuation ratios are positively skewed. With lognormal shocks, OLS yields strongly upward-biased estimates of class valuations, between 0.02 and 0.11, or about 4% of the true multiple. The drawbacks of OLS regressions become more pronounced in Panel B, where we assume a higher cross-sectional variation in excess values of 0.6. In this case, the bias reaches 20%. Valuation ratios are known to be positively skewed, and our simulation evidence thus strongly suggests that OLS should not be used to obtain class valuations. In contrast, estimates from median regressions are unbiased and, similar to excess values, remain robust to different distributional assumptions. Overall, the results of the Monte Carlo exercise show that valuation ratios of classes can be robustly estimated using median regressions.

II. Sample and Data

A. Firms and Divisions

We obtain firm-level accounting variables and SIC industry classifications from Compustat. We obtain division-level variables from the Compustat Segment files. Our sample period starts in 1978, when Compustat segment data become available, and ends in 2013. Following the literature, we exclude firms with at least one division in the financial sector, (SIC codes 6000-6999), in agriculture (SIC codes lower than 1000), and in government, other non-economic activities, or unclassified services (SIC codes 8600, 8800, 8900, and 9000).

Since we are interested in studying division valuations, we exclude firms whose sales, assets, or operating profits at the level of business segments are unavailable on Compustat. We also exclude divisions with zero sales, such as corporate accounts. Following the literature, we further require total sales from the Compustat annual files to be greater than $20 million and within one percent of the sum of division sales.

We define a conglomerate as a firm that operates in at least two distinct classes, and our sample size therefore changes according to class definitions. When classes are based on 4-digit SIC codes, our sample includes 3,432 conglomerates (18,437 firm-year observations) and 12,481 divisions (51,109 division-year observations). In this sample, an average (median) conglomerate owns book assets valued at $2.67 ($0.64) billion of CPI-adjusted 2004 dollars, has a Tobin's q of 1.46 (1.27) based on asset multiples and of 1.36 (1.12) based on sales multiples, operates in 2.77 (2) business segments, and has annual capital expenditures of 7.95 (4.11) percent of sales. An average (median) division has annual sales of $1.24 ($0.22) billion and owns book assets valued at $1.29 ($0.21) billion. These numbers are consistent with the numbers reported in the literature (e.g., Custodio, 2014).

B. Excess Values

To compare our estimates with those reported in the literature, we begin our empirical analysis by calculating conglomerates' excess values following the method used by Berger and Ofek (1995). Specifically, we define excess value as the natural log of the ratio of a firm's actual value to its imputed value, using both sales and assets multiples. We calculate excess values using the 4-digit and 2-digit SIC codes and the Fama-French 10 industries.[4]

When using the 4-digit SIC codes, we follow Berger and Ofek (1995) and calculate Tobin's q as the median q of all standalone firms in the finest SIC group with at least five firms. A shortcoming of this industry classification, however, is that the number of conglomerate divisions that operate in each industry in a given year is small, with the median number of divisions per industry-year of just two. Therefore, our subsequent empirical analyses rely on the 2-digit SIC codes and the Fama-French 10 industries, which are coarse enough to ensure that a sufficiently large number of divisions operate in each industry and thus that the $\tilde{W}$ matrix of industry weights for conglomerates is well populated and has full column rank.[5] A benefit of this coarse classification is that our analysis is less exposed to the criticism of Villalonga (2004a,b), who shows that the SIC code assigned by Compustat frequently is different from the code of the division's largest industry. While a substantial number of divisions may be misclassified into wrong 4-digit SIC codes, they likely remain in the same Fama-French industry.

Table II reports median excess values, by year and from the pooled sample, for the three industry classifications. The first three columns correspond to the 4-digit SIC code classification. Based on this definition, the median excess value from 1978 to 2013 is, on average, -15% (-10%) when sales (asset) multiples are used. These estimates are similar to those reported in Berger and Ofek (1995).

The remaining columns of Table II report median excess values for the 2-digit SIC

[4]The industries are defined in Appendix A.

[5]We also consider the Fama-French five, seventeen, and thirty industries. A finer classification leads to missing observations for some industry-years but produces qualitatively similar results.

and the 10 Fama-French industries. Across each year and in the pooled sample, both of these classifications produce excess value estimates that are similar to those in the 4-digit SIC industries. For example, based on the 10 Fama-French industries, the median excess value is, on average, -13% (-7%) when sales (asset) multiples are used. Note that sample size (12,056 observations) is about a third smaller relative to the 4-digit SIC code classification (18,437 observations) since there are fewer firms with divisions operating in two distinct 10 Fama-French industries than in two distinct 4-digit SIC code industries.

III. Industry Analysis

We begin our analysis by presenting evidence on the average valuation multiples of divisions relative to standalone firms across industries. Our focus on industry-level valuation estimates is motivated by the standard definition of a diversified firm in corporate finance: a firm that operates in more than one industry. As suggested in Coase (1937) and Maksimovic and Phillips (2007), corporate diversification matters only if the conglomerate's industry composition affects its transaction costs and hence its optimal boundaries. Thus, for corporate diversification to be of interest, it must be that the industry composition of conglomerates is related to firm value.

Table III shows the estimated average valuation multiples of conglomerate divisions, standalone firms, and the resulting relative division values (RDVs) across the 10 Fama-French industries. Panels A and B correspond to sales and asset multiples, respectively.

Similar to Berger and Ofek (1995), we define the RDV of an industry as the log of the ratio of valuation multiples of conglomerate divisions and standalone firms.[6] To establish the statistical properties of the time-series average of RDVs, we rely on bootstrapping. In particular, each year we resample residuals of the quantile regression 1,000 times, re-estimate the regression, and compute average RDVs for each sample. The

[6]Estimated conglomerate multiples could be negative due to estimation error or because conglomerates support divisions with negative values. Throughout our analysis, our estimates are positive, but we nonetheless confirm that our findings are robust to defining RDV as the difference rather than the ratio of multiples.

standard errors of RDVs are calculated using the standard deviation of the bootstrapped estimates. To account for a possible asymmetric distribution of the test statistic, we also report bootstrapped p-values for the test that RDVs are less than or equal to zero.

There are two main takeaways from Table III. First, the valuation multiples of conglomerate divisions are significantly different from the valuation multiples of standalone firms. Based on the sales multiples in Panel A, the correlation between the valuation of divisions and standalone firms ranges from 0.94 in the manufacturing sector to 0.22 in the health sector. Furthermore, RDVs are highly statistically significant in all sectors except manufacturing. These estimates suggest that industry multiples of standalone firms are noisy proxies for division multiples and introduce large measurement errors.

Second, Table III shows that the valuation multiples of divisions relative to standalone firms vary considerably across industries. Based on the sales multiples in Panel A, seven industries have a significantly negative RDV, with the largest discounts in the energy (-56%), high-tech (-37%), and healthcare (-26%) industries. In contrast, conglomerate divisions in two industries show substantial premia. Divisions in the nondurable goods sector are valued at a 19% premium and divisions in the telecommunications sector are valued at a 12% premium. The evidence is qualitatively similar based on the asset multiples in Panel B.[7]

Table III also reveals considerable within-industry variation in RDVs over time. Based on Panel A, the standard deviation in RDVs within industries ranges from 11% in the manufacturing and energy sectors to 38% in the healthcare sector. This variation is also illustrated in Figure 1, which shows RDVs based on sales multiples (solid blue line) and asset multiples (dashed red line) for each industry.

Overall, these findings suggest that the aggregate estimates of conglomerate value provided by Berger and Ofek (1995) and the numerous studies that follow do not

[7]Valuation ratios based on assets multiples are more closely aligned with the theoretical Tobin's q, which relies on the replacement value of capital. However, Custodio (2014) offers a caveat by noting that the accumulation of goodwill in merger and acquisition accounting biases the book value of assets upwards. Since conglomerates on average make more acquisitions, their assets will be more inflated. Conglomerates also have flexibility in allocating assets across divisions. We therefore follow Custodio's suggestion and focus our subsequent analysis on sales multiples.

reflect the considerable within-conglomerate variation in valuation. In particular, our disaggregated estimates indicate that the value of conglomeration varies systematically across industries.

Our findings have broad implications for prior research on corporate diversification. For example, theories of cross-subsidization of weak divisions (e.g., Rajan, Servaes, and Zingales (2000), Scharfstein and Stein (2000)) would have to vary systematically across industries. Similarly, explanations based on the endogenous decision to diversify via acquisitions (e.g., Graham, Lemmon, and Wolf (2002), Campa and Kedia (2002)) would require systematic differences in valuations of acquirers or targets across industries.

Moreover, the variation in RDVs across industries also suggests that one needs to exercise caution in extrapolating results based on industry-specific analyses. For example, a number of studies have used the Longitudinal Research Database to investigate the value of internal capital markets (e.g., Maksimovic and Phillips (2002)) and the productivity of conglomerate divisions (e.g., Schoar (2002)). However, this database tracks only manufacturing plants, a limitation that the authors of these studies acknowledge. While our estimates confirm that there is no significant discount in the manufacturing sector, they at the same time uncover deep discounts in the energy and hi-tech sectors and large premiums in the non-durable and telecommunication sectors.

Our findings also have implications for Villalonga's (2004a) explanation that the diversification discount may arise due to strategic accounting. Under this view, diversified firms aggregate their activities into segments in ways that may make them appear as artificially low performers relative to standalone firms in the same industries. However, our industry-by-industry valuation estimates reveal considerable heterogeneity across industries, suggesting that conglomerate valuations cannot be explained by strategic accounting alone.

One caveat with this analysis is that the value of operating an industry inside the conglomerate can be affected by its other divisions. Hoberg and Phillips (2015), for example, show that conglomerates tend to operate in economically related industries.

Thus, a conglomerate's choice of industries is not random, and endogenous matching can create additional value through synergies.

To assess this possibility, we study within-conglomerate cross-industry pairs. Each column in Panel A of Table IV corresponds to an industry, and each row reports the proportion of conglomerates that also have divisions in the industry indicated by the row. Consistent with nonrandom industry matching, we find that industry-pairs are not equally distributed inside conglomerates. This can be seen from the nonuniform distribution within each row. For example, 52% of conglomerates with a division in utilities also operate one in energy, whereas only 3% of conglomerates with a division in nondurables do.

Importantly, however, we find an insignificant relation between the value of divisions and their pairing with other industries inside the conglomerate. Panel B of Table IV shows average RDVs that are obtained by omitting from the sample all conglomerates that operate in the industry indicated in the row label. For example, when the sample is limited to conglomerates that have a division in the nondurables industry but not in the durables industry, the nondurables divisions are valued at a premium of 18% relative to standalone firms. Across all industries, the exclusion of industry pairs does not have a sizeable effect on the average RDV. These exclusions generate a small variation in RDVs within each industry (average standard deviation = 3.7%). Furthermore, the RDVs estimated after excluding industry pairs are statistically different from the full-sample RDVs at the 5% level only in 6 out of 90 cases (6.7%). Overall, this evidence suggests that the cross-industry variation in RDVs continues to hold after accounting for the endogenous within-conglomerate industry matching.

Taken together, the results in this section suggest that conglomerate-implied valuations vary systematically across industries and are substantially different from the commonly used industry valuations based on standalone firms. In the next section, we investigate the implications of these findings for conglomerate investment and internal capital allocation.

IV. Investment Decisions of Conglomerates

Neoclassical theory suggests that, absent financial frictions, investment should depend only on investment opportunities measured by marginal Tobin's qs. Shin and Stulz (1998) and Ozbas and Scharfstein (2010) use this neoclassical relation to study the efficacy of conglomerates' internal capital allocation. They estimate a division's q as the median q of standalone firms in its industry.

Ozbas and Scharfstein (2010) compare the sensitivity of investment to Tobin's q in conglomerate divisions and standalone firms. They find that investment is less sensitive to q in conglomerate divisions than in standalone firms. These results are broadly interpreted as evidence that conglomerates overinvest when opportunities are low and underinvest when they are high.

Rather than comparing investments of conglomerates and standalone firms, Shin and Stulz (1998) focus solely on divisional investments, estimating their sensitivity to industry Tobin's q and divisional cash flows. They argue that if internal capital markets are working efficiently, (1) divisional investment will depend mostly on the cash flow of the firm as a whole and not on divisional cash flow, and (2) the sensitivity of investment to cash flow will be lower in divisions with a high q. In contrast, they find that divisional investment is more sensitive to its own cash flow than the cash flow of the firm as a whole, and that the sensitivity of a division's investment to cash flow does not depend on the quality of its investment opportunities. They interpret their evidence as consistent with inefficient internal capital markets and socialism – divisions are treated alike irrespective of their investment opportunities.

One concern with these studies is their use of standalone firms to proxy for Tobin's q of conglomerate divisions. Whited (2001) and Maksimovic and Phillips (2002) demonstrate that estimates of investment opportunities derived from qs of standalone firms are inappropriate for the study of investment by conglomerate divisions. In particular, they show that these estimates suffer from measurement errors that arise due to potentially unobservable differences between conglomerate divisions and standalone firms.

In contrast, the division-level estimates of multiples generated by our method do not rely on standalone firms. We use these multiples to investigate differences in q-sensitivity of investment between conglomerates and standalone firms (Ozbas and Scharfstein, 2010), and the sensitivity of conglomerates' internal capital allocations to divisional qs and cash flows (Shin and Stulz, 1998).

Columns (1)-(4) of Table V compare the sensitivity of investment to Tobin's q in conglomerate divisions and standalone firms. As in Ozbas and Scharfstein (2010), the dependent variable is capital expenditures over sales, the regressions include year and industry fixed effects, and the standard errors are clustered by industry-year. In columns (1) and (3), the key explanatory variables are q^{SA}, the industry median q of standalone firms, and its interaction with SA, an indicator variable equal to one for standalone firms and zero for conglomerate divisions. Hence, the coefficient on q^{SA} represents the q-sensitivity of investment of conglomerate divisions, and the interaction term captures the incremental sensitivity of standalone firms. In column (3), we also include the ratio of cash flows to sales, CFS. Following Ozbas and Scharfstein (2010), we normalize by sales instead of assets because conglomerates may have more discretion in allocating assets across divisions.

The results in columns (1) and (3) are similar to those obtained by Ozbas and Scharfstein (2010). Conglomerate divisions exhibit lower q-sensitivity of investment than do standalone firms, as evidenced by a statistically significant positive coefficient on the interaction term $q^{\text{SA}} \cdot SA$. Based on column (3), the sensitivity of conglomerate investment to q^{SA} is 2.8% lower than that of standalone firms.

In columns (2) and (4), we augment the regressions with q^{C}, the division-level estimates of Tobin's q generated by our method. We find that investment of standalone firms depends on q^{SA}, but is insensitive to q^{C}. In contrast, investment of conglomerate divisions is highly sensitive to q^{C}, but is unrelated to q^{SA}. These results are evidenced by the large and significant coefficients on q^{C}, and insignificant coefficients on q^{SA}.

Based on column (4), the sensitivity of a division's investment to our estimate of the conglomerate-implied q is 2.9%, statistically significant at the 1% level (t-stat = 3.31).

These results indicate that conglomerate investment is more sensitive to investment opportunities measured using conglomerate firms than to industry multiples from standalone firms. This is more consistent with Whited's (2001) critique that investment opportunities are measured with error and less consistent with the hypothesis that conglomerates invest inefficiently.

In columns (5) and (6) of Table V, we investigate the sensitivity of division investment to cash flows using the sample of conglomerate divisions as in Shin and Stulz (1998). These analyses allow for a division's investment to depend on its own investment opportunities and cash flows, as well as those of other divisions (q^{SA}_{-j}, q^{C}_{-j}, and CFS_{-j}). The investment-cash flow sensitivity can further depend on the division's investment opportunities ($q^{\text{SA}} \cdot CFS_{-j}$ and $q^{\text{C}} \cdot CFS_{-j}$). When we use industry multiples (q^{SA}) to proxy for a division's investment opportunities in column (5), our results are similar to those of Shin and Stulz (1998). First, a division's investment is more sensitive to its own cash flow than to the other divisions' cash flows. Second, the sensitivity of a division's investment to other divisions' cash flows is not lower when it has better investment opportunities. As noted above, these findings are traditionally interpreted as evidence against efficient internal capital markets.

However, when we augment the specification with our division-level multiples q^{C} in column (6), we find different results. A division's investment is more sensitive to other divisions' cash flows than its own cash flow (coefficients of 0.168 vs. 0.095). Further, the sensitivity to other divisions' cash flows is lower when investment opportunities are higher. This can be seen from the negative coefficient (-0.333) on the interaction term $q^{\text{C}} \cdot CFS_{-j}$. This evidence is broadly consistent with efficient internal capital allocation.

Overall, we obtain strikingly different results about a division's sensitivity of investment when we use our division level q, q^{C}, rather than the industry median q of standalone firms, q^{SA}. These results suggest that prior findings should be interpreted with caution because they may arise due to measurement error in Tobin's q rather than inefficient allocation of capital inside conglomerates. Moreover, these findings suggest that our method generates clean measures of investment opportunities inside conglomerate firms.

V. Division Characteristics and Valuations

We now analyze the cross-sectional variation in division valuation multiples, and evaluate our findings in light of the prominent theories of conglomeration. To this end, we group conglomerate divisions either by division-level or by industry-level observable characteristics, and compare the average valuation multiples across the groups.

The analysis of the association between division attributes and valuation outcomes is subject to two sources of endogeneity: (1) simultaneity, or reverse causality, and (2) omitted variables. The first issue arises because an empirical relation between division attributes and valuations may indicate that the attributes respond to valuations rather than cause them. For example, valuations may affect division size. The second issue arises because a missing factor could drive division valuations while being correlated with other division attributes. While we mitigate these concerns by using industry-level attributes and regulatory shocks, we caution the reader that our tests are meant to offer suggestive evidence on division-level valuations. Importantly, this evidence cannot be provided by existing measures of conglomerate value.

A. Industry Conditions

We start by investigating how the valuation of conglomerate divisions varies with industry conditions. Table VI sorts 2-digit SIC industries into five groups on two measures of industry conditions: last year's annual industry sales growth (Panel A), and expected growth, defined as the industry median analysts' forecasts of growth in earnings per share (Panel B).

Table VI shows that RDVs are higher in weak industries. The average RDV is -9% in industries with low sales growth, while it is -15% and -28% when sales growth is medium and high, respectively. The difference in RDVs between high-growth and low-growth industries is economically large (-19%) and highly statistically significant, as every bootstrapped sample resulted in a negative estimate.

A similar picture emerges when we consider expected, rather than realized, growth in Panel B. In industries with low expected earnings growth, divisional valuations are 11% higher than those of standalone firms. Divisional valuations decrease, while standalone valuations slightly increase, as we move to high-growth industries, where the average RDV is -19%. Overall, the difference in RDVs between low- and high-growth industries is highly statistically significant at 30%.[8]

These findings are consistent with the evidence in Gopalan and Xie (2011), who show that conglomerate divisions in industries suffering extreme distress have higher sales, stronger cash flow growth, and spend more on R&D than do standalone firms. We provide complimentary evidence by showing that market valuations reflect this stronger relative performance of conglomerate divisions in distressed industries.

These results can be consistent with both the bright side view and the dark side view of internal capital markets. According to the bright side view, divisions in distressed industries would benefit from being part of a conglomerate through (1) an ability to raise more capital, and (2) an efficient internal reallocation of capital. An implication of this hypothesis would be that conglomerate firms are better-suited to overcome economic difficulties through cross-divisional coinsurance and internal transfers. Conversely, according to the dark side view, conglomerate firms would inefficiently support divisions in weak industries due to agency problems and the rent-seeking behavior of divisional managers.

To distinguish between the two possibilities, Table VII assigns conglomerate divisions into three groups. The first group includes divisions that are directly affected by

[8]It is interesting to consider the impact of leverage on RDVs, especially in light of the argument of Mansi and Reeb (2002) that the difference between market and book values of debt contributes to the conglomerate discount. In distressed industries, the market value of debt can be expected to be particularly low relative to the book value of debt for standalone firms, whereas the wedge should be smaller for the debt of diversified conglomerates. The RDVs we obtain for distressed industries thus likely understate RDVs obtained based on market values. We therefore expect the actual effect of industry conditions on RDVs to be even larger than we document.

adverse industry conditions because they operate in weak industries, defined as those in the low growth quintile in the previous analysis. The second group includes all indirectly affected divisions, defined as all other divisions in conglomerates with divisions in the first group. The third group includes all unaffected divisions, that is, divisions in conglomerates that do not operate in the weak industries.

The above classification of conglomerate divisions allows us to identify the value implications of internal transfers for both directly affected and indirectly affected divisions, and benchmark them against unaffected divisions. By doing so, we can determine the efficiency of the cross-subsidization of divisions in weak industries.

The evidence in Table VII suggests that directly affected divisions benefit at the expense of other divisions. In particular, indirectly affected divisions have lower valuation multiples than do their unaffected counterparts. For example, when industry conditions are measured by sales growth (Panel A), indirectly affected divisions are valued at 87% of sales, or 26% lower than corresponding standalone firms. Unaffected divisions, on the other hand, trade at 91% of sales, only 21% lower than standalone firms.

We do not find, however, any evidence that internal capital flows are collectively inefficient. Rather, we find that they enhance overall firm value. While indirectly affected divisions are valued 4% lower than unaffected divisions (87% vs. 91% of sales), this loss is more than offset by the gain in the value of divisions in weak industries.[9] We find similar results when we measure industry conditions by analyst growth forecast (Panel B).

Taken together, the estimates in Tables VI and VII suggest that conglomerate divisions operating in weak, low-growth industries have higher valuation multiples than do standalone firms. While these higher RDVs coincide with lower multiples in other

[9] The magnitude of this value gain is difficult to quantify precisely. We observe that the difference in value between the directly affected divisions and unaffected divisions is $0.96 - 0.91 = 0.05$. Further, directly affected divisions on average account for 54% of conglomerate sales (untabulated). This suggests that the value gain in the directly affected divisions, $0.05 \cdot 0.54 = 0.027$, more than offsets the value loss in the indirectly affected divisions, $(0.87 - 0.91) \times (1 - 0.54) = -0.018$. This estimate constitutes a lower bound as it is natural to expect that directly affected divisions should be trading at lower multiples due to weak industry conditions. Conducting a similar calculation on RDVs instead of division valuation multiples suggests a large gain in the relative value of the overall conglomerate.

divisions of the conglomerate, the net effect appears to be positive. These findings are more consistent with the bright side view of conglomerates, and their ability to support operations through financing capacity and internal capital reallocation.

B. Investment Intensity

According to the bright side view of conglomeration, access to internal capital markets mitigates financial constraints, and internal budgeting allows capital to be allocated more efficiently (Stein, 2003). In the cross-section of divisions, this hypothesis suggests that financially constrained divisions with high demand for capital should benefit most from being part of a conglomerate.

Ideally, to apply our method we would like to identify financial constraints at the division- or industry-level. However, typical measures of financial constraints, such as the indices proposed by Kaplan and Zingales (1997), Whited and Wu (2006), or Hadlock and Pierce (2010) are not suitable measures in our setting as they aim to measure firm-level financial constraints. Instead, we measure the demand for capital using the industry median capital expenditures (Panel A of Table VIII). We also consider a broader measure of investment that adds acquisitions and deducts sales of property, plants, and equipment (Panel B).

Table VIII compares RDVs across divisions operating in industries with low, medium, and high demand for capital. The results indicate that divisions in investment-intensive industries are valued at substantial premia relative to their standalone peers. For example, estimated RDVs in Panel A are 6% and 11%, both statistically significant, for the top two quintiles. By contrast, the bottom two quintiles have RDVs of -31% and -29%. The difference in RDVs between the top and bottom quintiles is 40% and is highly statistically significant. We obtain similar results based on the comprehensive measure of investment in Panel B.

To the extent that our industry-wide measures of investment intensity capture efficient investment levels, these results provide support for the bright side view of internal capital markets. Inefficient cross-subsidization can generate our effects only if industry investment levels of standalone firms are correlated with intra-conglomerate rent-seeking.

Taken together, the results thus far indicate that conglomeration facilitates efficient investment in weak or capital-intensive industries. Next, we turn to investigate conditions under which conglomerates may operate inefficiently.

C. Innovation and Competition

The dark side view of conglomeration suggests that the rent-seeking behavior of divisional managers distorts capital budgets (Scharfstein and Stein (2000), Rajan, Servaes, and Zingales (2000)). We investigate this view by studying divisional values in innovative or competitive industries, where allocation distortions would have potentially severe value implications.

We begin our analysis by studying the link between divisional valuations and innovation. As Seru (2014) points out, the information asymmetry that accompanies innovation activities may exacerbate the agency problems and inefficiencies in conglomerate investment. We therefore posit that divisional valuations relative to standalone firms would be lower in innovative industries.

In Table IX, we compare division valuations across different levels of innovation activity. In Panel A, we use the industry median R&D intensity, defined as the ratio of R&D expenditures to sales, following Chan, Lakonishok, and Sougiannis (2001) and Leary and Roberts (2010). In Panel B, we measure innovation as the industry median patent intensity, computed as the number of patents granted divided by the book value of the firm, following Deng, Lev, and Narin (1999). While R&D intensity measures the inputs for innovation production, patent intensity measures the production output.

Across both Panels, we find that conglomerate divisions in innovative industries have lower RDVs. In Panel A, RDVs range from -13% to -2% for industries with low and medium R&D intensity, and drop sharply to -33% in R&D-intensive industries. The difference in RDVs between high and low R&D intensity industries is -20%. The results based on patent intensity in Panel B mirror those in Panel A, but the main effects are even larger, with the difference in RDVs reaching a staggering -73%.

Our evidence is consistent with the findings in Seru (2014), who shows that recently acquired divisions produce fewer and less-novel innovations. While Seru (2014) establishes causally that conglomerates stifle innovation, we complement his results by showing that prices of divisions in innovative industries are heavily discounted.

In Table X, we investigate the link between RDVs and product market competition. Panels A and B use Herfindahl indices over market equity and assets, respectively. Panel C shows results for the number of competing firms in the industry, and Panel D is based on the Li, Lundholm, and Minnis (2013) competition measure derived from textual analysis of firms' 10-K filings.

We find a strong negative and monotonic relation between the degree of product market competition and RDVs. Across all panels of Table X, divisions in noncompetitive industries trade at RDVs close to zero. In contrast, the RDVs in highly competitive industries are negative and significant, both economically and statistically. In particular, RDVs in the most competitive industries vary from -22% to -25% based on the Herfindahl indices, and reach -32% based on the number of competing firms.

An alternative interpretation of these findings is that standalone firms that are unable to compete in competitive industries offer themselves for sale to conglomerates, thereby endogenously generating the relation between industry competition and RDVs that we document. To provide causal evidence that competition erodes relative division values, we study exogenous increases in competition following industry deregulation, using the sample of deregulation events from Table 3 of Harford (2005).[10]

To estimate RDVs for an industry undergoing deregulation, we group all divisions into two classes: divisions in the affected industry, and the remaining ones.[11] Using division valuations and median valuations of standalone firms in the affected industries,

[10]Harford's sample contains 19 deregulation events. Consistent with our analysis in the rest of the paper, we exclude events in the banking industry. To minimize estimation error, we also drop industry-years with fewer than 25 conglomerate divisions. For deregulation events in consecutive years we only keep the earliest one. Our final sample consists of 10 events. See Appendix C for details.

[11]An alternative approach involves using 11 classes: the ten Fama-French industries underlying our earlier analysis plus the event industry. While this approach allows for a better control of industry effects, in this context it is less suitable as the larger number of parameters reduces estimation efficiency.

we derive two variables of interest. The first measure is the difference in growth rates in valuation ratios of conglomerate divisions and standalone firms from the year prior to deregulation to the end of the event year. The second measure is the difference in RDVs prior to and following deregulation.

Table XI shows the results for the two difference-in-differences estimators. The valuation of conglomerate divisions decreases on average by 7.8% following deregulation. In contrast, the valuation of standalone firms is unaffected. Furthermore, the valuation of divisions decreases in eight of the ten events considered, and in 87% of the bootstrapped samples. RDVs on average decrease by 10.2% following industry deregulations. This estimate is economically large and statistically significant at the 10 percent level both under the asymptotic normal distribution assumption and in the bootstrapped sample.

Our findings are consistent with the predictions of Matsusaka and Nanda (2002), who show that the flexibility available to the conglomerate firm headquarters creates a strategic disadvantage in product market competition. A rival firm will not enter a market if it believes the incumbent firm will be investing heavily in that market. However, the conglomerate firm cannot credibly commit to such investment because it responds to investment opportunities in different industries. Empirically, our results extend the analysis of Santalo and Becerra (2008) who compute a weighted average of division competition measures for each conglomerate and show that conglomerate discounts increase with competition.

D. Core vs. Peripheral Divisions

The large diversification discount documented in prior research does not imply that diversification destroys value. If the sample of conglomerates is systematically different from median standalone firms, the matching procedure employed in the literature can lead to wrong conclusions. For example, Graham, Lemmon, and Wolf (2002) show that excess values of firms that expand via diversifying acquisitions decline because they acquire already-discounted business units and not because diversification destroys value. Similarly, Campa and Kedia (2002) and Villalonga (2004a) argue that firms that already have low valuations are those that choose to diversify in the first place. Their empirical analyses show that conglomerate discounts disappear after controlling for this selection effect.

These arguments are formalized theoretically by Matsusaka (2001). He develops a dynamic model in which diversification is the optimal outcome of a search process by which firms seek to acquire businesses that are good matches for their capabilities. In his model, diversified firms are discounted because they choose to diversify when their value decreases and not because they make bad diversification decisions.

We contribute to this discussion by applying our method to separately estimate the valuations of core and peripheral divisions. If the diversification discount originates from conglomerates that systematically acquire discounted business units, we expect to see the largest discounts in the divisions that joined the conglomerate by means of an acquisition. These divisions are typically peripheral and small. On the other hand, if firms choose to diversify when their value decreases, we expect to see the largest discounts in the core divisions.[12]

We classify divisions into core and peripheral in three different ways. First, we designate divisions as core if their 4-digit SIC code from the Compustat Industry Segment files matches the 4-digit historical SIC code that Compustat provides for the company as a whole. This approach seems closest to the idea of core and periphery but has two disadvantages. First, historical SIC codes are only available after 1987, reducing our sample period by nine years. Second, for about half of the conglomerates, no division matches the firm-level SIC code.[13] To overcome these disadvantages, we use two alternative definitions of core divisions based on the size of the divisions. Specifically, we define core divisions as the largest divisions based on assets or sales within the conglomerate.

One concern with our size-based measures is that with decreasing returns to scale, as

[12] Our estimates are based on market values and hence reflect any valuation effects of expected internal capital reallocations. Therefore, even if acquisition targets have low valuations, as in Graham, Lemmon, and Wolf (2002), their post-acquisition value can be higher. However, a capital transfer from big to small divisions will asymmetrically affect their valuations, significantly increasing the value of small divisions and only weakly decreasing the value of big divisions.

[13] This is because Compustat assigns SIC codes after an internal iterative process that sometimes results in a coarser 3- or 2-digit conglomerate SIC code. See Guenther and Rosman (1994) for a detailed explanation.

in Gomes and Livdan (2004), we would expect larger divisions to have lower valuations. To address this concern, we first note that the within-conglomerate difference in relative size is dwarfed by the across-conglomerate variation in size. In other words, small peripheral divisions in large conglomerates are much larger than big core divisions in small conglomerates. Nevertheless, we control for size by computing standalone valuations only using firms whose size falls within the support of the size distribution of the conglomerate divisions in each group.

Table XII presents the results. Across all three measures, core divisions have significantly lower valuations than peripheral divisions. When we identify core divisions using SIC codes (Panel A), they are valued at 97% of sales, while peripheral divisions are valued at 115% of sales. The 17% difference is economically large and statistically significant with a p-value of 0.04. These valuation effects also carry over to RDVs, where core divisions are valued at a 23% discount, while the discount of peripheral divisions is only 11%.

We obtain similar results when core divisions are defined based on the relative size of their assets (Panel B) or sales (Panel C). For example, in Panel B, the RDV of core divisions is -23%, whereas the RDV of peripheral divisions is -14%. The difference is statistically significant at the 1% level.

Overall, our findings suggest that conglomerate discounts are concentrated in the conglomerate's core line of business. In contrast, discounts in non-core divisions are significantly lower. These findings are consistent with Matsusaka's (2001) optimal search model, in which diversification is a consequence of low valuation rather than the reason for it.

These findings are also related to the model in Maksimovic and Phillips (2002). In their model, specialization is optimal if the firm is much more productive in one industry than the other; diversification is optimal if the productivities are similar. Thus, the decision to diversify depends in part on the firm's comparative productivity in the two industries. An implication of this result is that, all else being equal, a conglomerate's larger segment is more productive than its smaller segment. In contrast, we find that smaller divisions are less discounted than larger ones.

VI. Conclusion

We propose a novel method to estimate the valuation multiples of conglomerate divisions. Our approach uses only standard data and does not rely on standalone firms, thus mitigating concerns about measurement errors that may arise due to unobservable differences between conglomerate divisions and standalone firms. It therefore provides clean estimates of intra-conglomerate valuation multiples that allow us to dissect conglomerates and investigate conglomerate investment decisions and value determinants.

We provide three main analyses. First, we find that valuations of conglomerate divisions differ considerably from commonly used industry-level valuation proxies. These division valuations vary across industries, ranging from deep discounts to large premiums relative to standalone firms. Second, we investigate investment policies and show that conglomerate investment is highly sensitive to division multiples and insensitive to industry multiples based on standalone firms used in prior studies. Third, in the analysis of conglomerate value drivers, we show that small non-core divisions and divisions in weak or investment-intensive industries have higher valuations, whereas divisions in innovative or competitive industries have lower valuations. These analyses provide new evidence on the investment policies and valuations of conglomerate divisions that cannot be obtained from traditional estimates of conglomerate value.

Given that our approach estimates valuation multiples at the granular level of a conglomerate division, it can be extensively applied to broaden our understanding of internal capital markets and of the value of corporate diversification. More generally, our approach can be adapted to other applications where unobservable attributes of parts may be extracted from their observable analogue of the whole.

VII. Appendix

A. Industry Definitions

The ten Fama-French industries are defined as follows:

1. NDur: Consumer non-durables – food, tobacco, textiles, apparel, leather, toys
2. Dur: Consumer durables – cars, TVs, furniture, household appliances
3. Manu: Manufacturing – Machinery, trucks, planes, chemicals, office furniture, paper, commercial printing
4. Enrg: Oil, gas, and coal extraction and products
5. HiTec: Business equipment – computers, software, and electronic equipment
6. Tlcm: Telephone and television transmission
7. Shop: Wholesale, retail, and some services (laundries, repair shops)
8. Hlth: Healthcare, medical equipment, and drugs
9. Util: Utilities
10. Oth: Other – mines, construction, building materials, transportation, hotels, business services, entertainment, finance (except SIC 6000-6999, 8600, 8800, 8900, 9000)

B. Data Definitions

- Industry conditions
  - Industry sales growth: year over year growth in total industry sales
  - Analyst growth forecast: industry median growth rate of earnings per share implied by median analyst forecasts
- Investment
  - Capital expenditures: capital expenditures divided by lagged assets
  - Investment: capital expenditures plus acquisitions minus sale of property, plant, and equipment, all divided by lagged assets
- Innovation
  - R&D intensity: R&D expenditures divided by sales (Leary and Roberts, 2010)
  - Patent intensity: number of patents granted divided by book value
- Competition

- Herfindahl index over market equity, adjusted for the number of firms in the industry
- Herfindahl index over total assets, adjusted for the number of firms in the industry
- Number of competing firms. When grouping 2-digit SIC industries into classes by the number of competing firms, we aim for an equal number of firms in each class rather than for an equal number of industries
- Li, Lundholm, and Minnis (2013) competition: measure based on textual analysis of 10-K filings, available for 1995-2009 from Feng Li's website

C. Industry Deregulation Events

- Entertainment (Industry 7 of Fama-French 48; all excluded due to small number of conglomerate divisions.)
  - 1981: Deregulation of radio (FCC)
  - 1984: Cable Television Deregulation Act
  - 1987: Elimination of fairness doctrine (FCC)
  - 1992: Cable Television Consumer Protection and Competition Act
- Petrol and Natural Gas (30)
  - 1981: Decontrol of crude oil and refined petroleum products (executive order)
  - 1989: Natural Gas Wellhead Decontrol Act of 1989
  - 1992: Energy Policy Act
- Utilities (31)
  - 1992: FERC Order 636
  - 1996: FERC Order 888
- Communications (32)
  - 1982: AT&T settlement
  - 1993: Elimination of state regulation of cellular telephone rates
  - 1996: Telecommunications Act
- Transportation (40)
  - 1984: Shipping Act
  - 1993: Negotiated Rates Act
  - 1994: Trucking Industry and Regulatory Reform Act. Excluded due to deregulation in previous year.

  - 1995: Interstate Commerce Commission Termination Act. Excluded due to deregulation in previous year.

- Banking (44; all excluded because our sample excludes financial firms.)
  - 1982: Garn-St. Germain Depository Institutions Act
  - 1991: Federal Deposit Insurance Corporation Improvement Act
  - 1994: Interstate Banking and Branching Efficiency Act

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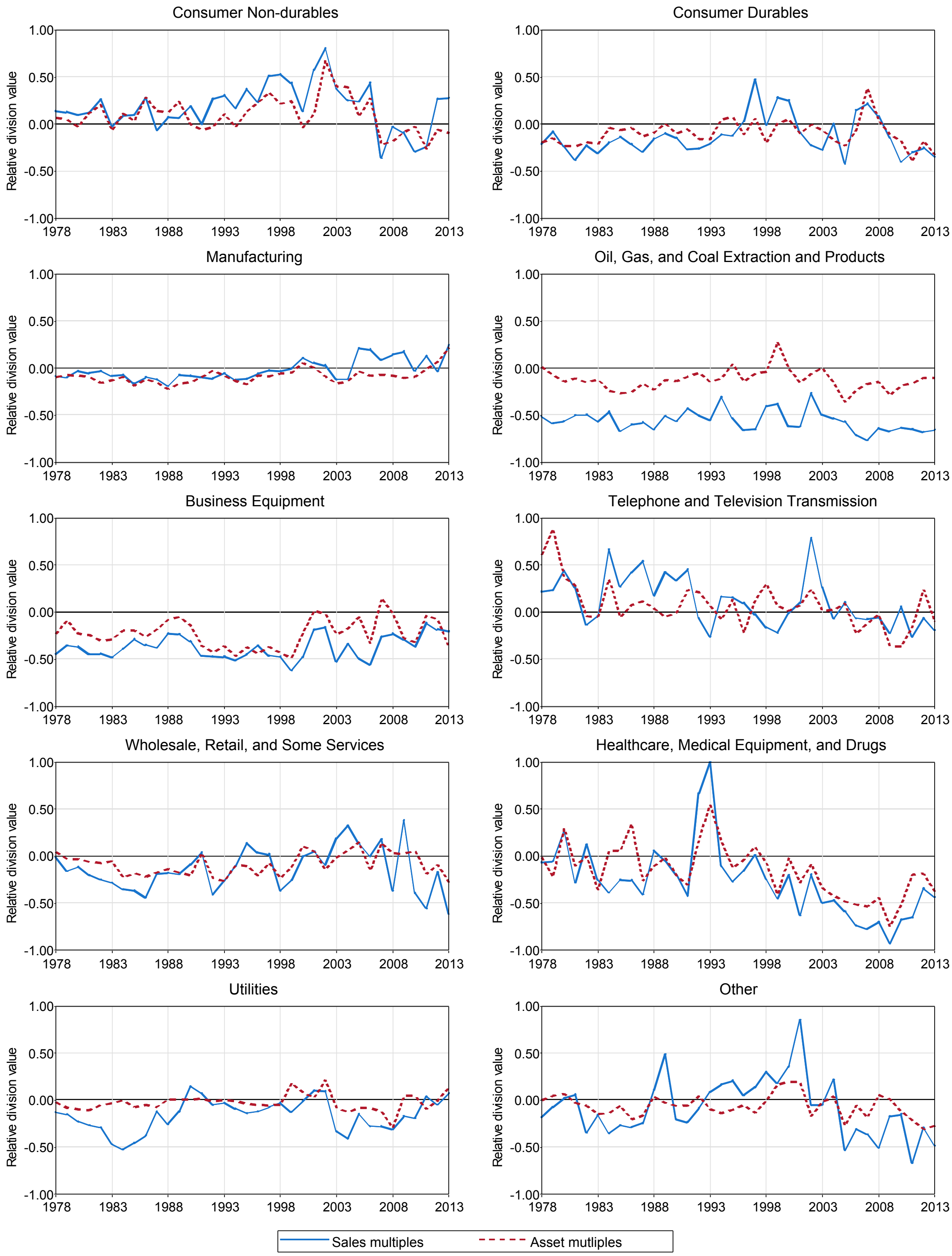

Figure 1. The Time-Series of Relative Division Values

This figure plots estimated relative division values based on sales (blue solid line) and asset (red dashed line) multiples for divisions in the ten Fama-French industries over time.

Table I
Simulation

This table reports the average and standard deviation of relative division values as well as the Berger and Ofek (1995) conglomerate excess values from 100,000 simulations of a cross-section of 500 conglomerates. Conglomerates have two (50%), three (33%), or four (17%) divisions, and each division's fundamentals are drawn from the exponential of a normal distribution with unit mean and a standard deviation of 0.8. The median class valuations are given by $q^{\mathrm{C}} = [0.5\ 1.0\ 1.5\ 2.0\ 2.5]'$ for segments in classes I to V respectively, and valuations are subject to a multiplicative shock with median of one. The conglomerate-level shock is drawn from either a normal distribution truncated at zero or a lognormal distribution, and has a standard deviation of 0.30 (Panel A) or 0.60 (Panel B).

Class	I	II	III	IV	V	Berger-Ofek
q^{C} of the class	0.5	1.0	1.5	2.0	2.5	excess value
A. Low variation in excess values ($\sigma = 0.30$)						
Normal distribution						
Median regression	-0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.05)	(0.07)	(0.08)	(0.10)	(0.11)	(0.02)
OLS regression	-0.00	0.00	0.00	-0.00	0.00	-0.05
	(0.05)	(0.06)	(0.07)	(0.08)	(0.09)	(0.02)
Log-normal distribution						
Median regression	0.00	0.00	0.00	0.00	0.00	0.00
	(0.05)	(0.07)	(0.08)	(0.10)	(0.11)	(0.02)
OLS regression	0.02	0.05	0.07	0.09	0.11	0.00
	(0.05)	(0.06)	(0.07)	(0.09)	(0.10)	(0.01)
B. High variation in excess values ($\sigma = 0.60$)						
Normal distribution						
Median regression	0.00	-0.00	0.00	0.00	-0.00	-0.00
	(0.10)	(0.12)	(0.15)	(0.17)	(0.20)	(0.03)
OLS Regression	0.00	-0.00	-0.00	0.00	-0.00	-0.18
	(0.08)	(0.09)	(0.11)	(0.13)	(0.15)	(0.03)
Log-normal distribution						
Median regression	0.00	0.00	0.00	0.00	0.00	-0.00
	(0.11)	(0.14)	(0.16)	(0.19)	(0.22)	(0.03)
OLS regression	0.10	0.20	0.30	0.39	0.49	-0.00
	(0.13)	(0.16)	(0.18)	(0.21)	(0.24)	(0.03)

Table II
Berger-Ofek Excess Values

This table reports conglomerate excess values (EV), by year and pooled, estimated as in Berger and Ofek (1995) for 4-digit SIC industries, for 2-digit SIC industries, and for the ten Fama-French industries. It also shows the number of conglomerates. Excess value calculations are based on sales or asset multiples.

	4-digit SIC codes			2-digit SIC codes			10 Fama-French industries		
	EV multiple		Number	EV multiple		Number	EV multiple		Number
Year	Sales	Assets	of firms	Sales	Assets	of firms	Sales	Assets	of firms
1978	-0.14	-0.06	966	-0.10	-0.04	807	-0.13	-0.03	654
1979	-0.15	-0.10	973	-0.14	-0.06	831	-0.12	-0.03	680
1980	-0.17	-0.09	936	-0.11	-0.04	793	-0.09	-0.03	643
1981	-0.17	-0.13	857	-0.16	-0.08	717	-0.15	-0.05	566
1982	-0.15	-0.11	799	-0.18	-0.09	674	-0.17	-0.06	526
1983	-0.22	-0.16	688	-0.28	-0.17	583	-0.23	-0.11	461
1984	-0.20	-0.13	703	-0.24	-0.13	588	-0.19	-0.08	466
1985	-0.20	-0.14	659	-0.25	-0.13	548	-0.21	-0.09	430
1986	-0.21	-0.14	581	-0.21	-0.11	486	-0.19	-0.09	376
1987	-0.20	-0.13	561	-0.20	-0.10	473	-0.17	-0.09	380
1988	-0.15	-0.08	581	-0.19	-0.08	474	-0.16	-0.06	373
1989	-0.11	-0.05	531	-0.12	-0.06	430	-0.09	-0.03	341
1990	-0.12	-0.08	545	-0.12	-0.07	437	-0.12	-0.07	352
1991	-0.14	-0.08	506	-0.17	-0.09	406	-0.12	-0.05	340
1992	-0.12	-0.07	518	-0.13	-0.10	407	-0.13	-0.04	332
1993	-0.14	-0.11	520	-0.16	-0.14	411	-0.12	-0.08	333
1994	-0.12	-0.13	536	-0.14	-0.16	426	-0.08	-0.09	343
1995	-0.12	-0.11	565	-0.13	-0.14	443	-0.09	-0.08	358
1996	-0.10	-0.09	541	-0.10	-0.11	434	-0.08	-0.07	357
1997	-0.09	-0.05	525	-0.05	-0.03	430	-0.06	-0.03	350
1998	-0.06	-0.05	619	-0.05	-0.05	477	-0.09	-0.04	387
1999	-0.08	-0.09	490	-0.09	-0.09	392	-0.10	-0.07	318
2000	-0.10	-0.07	361	-0.09	-0.09	303	-0.07	0.04	229
2001	-0.11	-0.08	325	-0.06	-0.07	257	-0.06	0.01	200
2002	-0.06	0.00	323	0.02	-0.01	254	0.04	0.02	205
2003	-0.23	-0.13	294	-0.19	-0.13	247	-0.08	-0.04	202
2004	-0.17	-0.12	299	-0.15	-0.12	239	-0.08	-0.05	183
2005	-0.21	-0.15	304	-0.19	-0.16	244	-0.11	-0.09	187
2006	-0.21	-0.14	317	-0.21	-0.15	245	-0.18	-0.12	188
2007	-0.16	-0.10	311	-0.16	-0.08	255	-0.18	-0.08	189
2008	-0.20	-0.10	321	-0.24	-0.09	252	-0.24	-0.10	198
2009	-0.14	-0.12	275	-0.19	-0.12	217	-0.13	-0.15	177
2010	-0.17	-0.14	261	-0.17	-0.17	209	-0.23	-0.14	168
2011	-0.15	-0.10	260	-0.17	-0.12	204	-0.21	-0.12	172
2012	-0.17	-0.12	293	-0.16	-0.08	230	-0.19	-0.11	198
2013	-0.26	-0.16	293	-0.19	-0.13	239	-0.21	-0.14	194
Average	-0.15	-0.10	512	-0.15	-0.10	418	-0.13	-0.07	335
Std. deviation	0.05	0.04		0.06	0.04		0.06	0.04	
Pooled	-0.15	-0.10	18,437	-0.15	-0.09	15,062	-0.13	-0.06	12,056

Table III
Industry Analysis of Division Values

This table reports for each of the ten Fama-French industries, values of conglomerate divisions and standalone firms, their time-series standard deviations and their correlation, as well as the relative division values (RDVs) and the associated bootstrapped standard errors, *p*-values, and time-series moments. The analysis is based on sales multiples (Panel A) and asset multiples (Panel B).

	NDur	Dur	Manu	Enrg	HiTec	Tlcm	Shop	Hlth	Util	Oth
A. Sales multiples										
Division value	0.90	0.62	0.83	1.32	0.98	3.19	0.41	1.38	1.75	1.06
Std. deviation	0.36	0.21	0.28	0.39	0.37	0.89	0.15	0.60	0.52	0.41
Standalone value	0.76	0.71	0.83	3.08	1.58	2.95	0.48	2.13	2.06	1.19
Std. deviation	0.25	0.16	0.21	0.80	0.54	0.99	0.12	0.91	0.40	0.41
Correlation	0.80	0.65	0.94	0.53	0.78	0.72	0.56	0.22	0.77	0.49
RDV	0.19	-0.13	-0.02	-0.56	-0.37	0.12	-0.13	-0.26	-0.16	-0.07
Std. deviation	0.24	0.20	0.11	0.11	0.12	0.27	0.23	0.38	0.17	0.31
Std. error	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.02)
p-value(RDV$\leq$0)	(0.00)	(1.00)	(0.81)	(1.00)	(1.00)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)
RDV, percentile 25	0.07	-0.26	-0.10	-0.65	-0.47	-0.07	-0.32	-0.48	-0.27	-0.29
RDV, median	0.18	-0.18	-0.05	-0.57	-0.37	0.10	-0.16	-0.26	-0.13	-0.12
RDV, percentile 75	0.29	-0.04	0.05	-0.50	-0.27	0.27	0.03	-0.08	-0.04	0.13
Avg. number of divisions	70	56	181	54	89	28	105	30	37	124
B. Asset multiples										
Division value	1.09	0.86	0.88	0.99	1.08	1.27	0.86	1.36	0.79	0.91
Std. deviation	0.29	0.19	0.17	0.23	0.24	0.34	0.17	0.38	0.10	0.16
Standalone value	0.99	0.95	0.96	1.13	1.43	1.20	0.94	1.68	0.81	0.98
Std. deviation	0.19	0.16	0.16	0.25	0.34	0.29	0.18	0.42	0.09	0.17
Correlation	0.73	0.71	0.87	0.83	0.54	0.71	0.73	0.19	0.69	0.72
RDV	0.09	-0.10	-0.08	-0.12	-0.23	0.08	-0.08	-0.16	-0.03	-0.06
Std. deviation	0.19	0.14	0.08	0.11	0.16	0.24	0.12	0.28	0.09	0.12
Std. error	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
p-value(RDV$\leq$0)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.01)	(1.00)	(1.00)	(0.96)	(1.00)
RDV, percentile 25	-0.03	-0.19	-0.14	-0.16	-0.36	-0.05	-0.18	-0.37	-0.08	-0.14
RDV, median	0.10	-0.10	-0.09	-0.14	-0.23	0.05	-0.09	-0.15	-0.04	-0.06
RDV, percentile 75	0.22	-0.02	-0.06	-0.07	-0.08	0.22	0.03	-0.01	0.01	0.02
Avg. number of divisions	70	56	181	54	89	28	105	30	37	124

Table IV
Industry Analysis of Division Values: Robustness

In Panel A, this table reports for each of the ten Fama-French industries (columns) the average proportion of conglomerates that also have divisions operating in others industries (rows). For example, 11% of conglomerates with a division in the NDur industry also have a division in the Dur industry. Panel B shows relative division values that are obtained by omitting from the sample all conglomerates that operate in the industry indicated in the row label. For example, when the sample is limited to conglomerates that have a division in industry NDur but not in industry Dur, the divisions in NDur are valued at a premium of 18% relative to stand-alone firms. One, two, and three asterisks indicate relative division values that are significantly different from those estimated in the full sample (Table III) at the 10%, 5%, and 1% levels, respectively. The bottom four rows show average, standard deviation, minimum, and maximum of these relative division values.

	NDur	Dur	Manu	Enrg	HiTec	Tlcm	Shop	Hlth	Util	Oth
A. Conditional distribution of industry pairings										
NDur		0.13	0.17	0.05	0.10	0.36	0.23	0.13	0.03	0.13
Dur	0.11		0.22	0.07	0.17	0.06	0.06	0.10	0.05	0.08
Manu	0.43	0.69		0.40	0.56	0.12	0.35	0.49	0.15	0.39
Enrg	0.03	0.06	0.12		0.04	0.07	0.13	0.06	0.52	0.17
HiTec	0.13	0.27	0.28	0.07		0.24	0.13	0.27	0.04	0.16
Tlcm	0.14	0.03	0.02	0.03	0.08		0.04	0.03	0.08	0.10
Shop	0.35	0.11	0.20	0.25	0.15	0.17		0.21	0.26	0.26
Hlth	0.06	0.06	0.08	0.03	0.09	0.04	0.06		0.03	0.04
Util	0.02	0.03	0.03	0.36	0.02	0.11	0.09	0.03		0.13
Oth	0.22	0.17	0.27	0.39	0.22	0.45	0.31	0.17	0.45	
B. Relative division values if industry pairs are omitted										
NDur		-0.12	-0.02	-0.55	-0.36	0.07	-0.09	-0.27	-0.15	-0.07
Dur	0.18		-0.06	-0.55	-0.36	0.12	-0.15	-0.25	-0.16	-0.03
Manu	0.21	-0.21		-0.50**	-0.34	0.13	-0.11	-0.37*	-0.17	0.00**
Enrg	0.19	-0.11	-0.04		-0.36	0.11	-0.12	-0.30	-0.06**	-0.11
HiTec	0.13	-0.07	-0.02	-0.57		0.24**	-0.13	-0.23	-0.14	-0.02*
Tlcm	0.08*	-0.12	-0.01	-0.56	-0.36		-0.11	-0.26	-0.18	-0.10
Shop	0.23	-0.14	0.02	-0.55	-0.36	0.20*		-0.22	-0.05***	-0.07
Hlth	0.15	-0.10	-0.03	-0.55	-0.38	0.16	-0.15		-0.16	-0.06
Util	0.19	-0.13	-0.01	-0.56	-0.37	0.11	-0.14	-0.27		-0.06
Oth	0.17	-0.14	-0.02	-0.56	-0.37	-0.02***	-0.08	-0.25	-0.21	
Average	0.17	-0.13	-0.02	-0.55	-0.36	0.12	-0.12	-0.27	-0.14	-0.06
St. Dev.	0.04	0.04	0.02	0.02	0.01	0.07	0.03	0.04	0.05	0.04
Min	0.08	-0.21	-0.06	-0.57	-0.38	-0.02	-0.15	-0.37	-0.21	-0.11
Max	0.23	-0.07	0.02	-0.50	-0.34	0.24	-0.08	-0.22	-0.05	0.00

Table V
q-sensitivity of Investment

This table reports results of panel regressions of the ratio of capital expenditures to sales on the following regressors: median q of standalone firms in the industry (q^{SA}), the conglomerates-based industry q computed following our method as in Table III (q^{C}), the ratio of cash flows to sales (CFS), the indicator for standalone firms (SA), and interaction terms. The subscript $-j$ indicates the corresponding measures for other divisions in the conglomerate. In regressions (1) through (4), the sample comprises of conglomerate divisions and standalone firms, and the denominator in CFS is division-level sales. In regressions (5) and (6), the sample contains only conglomerate divisions, and the denominator in CFS is conglomerate-level sales. The regressions include year and industry fixed effects. The t-statistics based on standard errors clustered by industry-year are shown in brackets.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
q^{SA}	0.027	0.010	0.032	0.015	0.016	0.001
	[3.60]	[1.05]	[4.53]	[1.63]	[1.79]	[0.08]
q^{C}		0.029		0.029		0.027
		[3.18]		[3.31]		[1.86]
CFS			-0.036	-0.040	0.112	0.095
			[-1.13]	[-1.23]	[2.57]	[2.06]
SA	-0.027	-0.019	-0.034	-0.026		
	[-4.66]	[-5.22]	[-5.58]	[-6.25]		
$q^{\mathrm{SA}} \cdot SA$	0.032	0.051	0.028	0.048		
	[4.93]	[4.42]	[4.34]	[4.34]		
$q^{\mathrm{C}} \cdot SA$		-0.032		-0.034		
		[-3.04]		[-3.34]		
$CFS \cdot SA$			0.083	0.087		
			[3.21]	[3.31]		
q^{SA}_{-j}					0.015	0.017
					[3.12]	[2.97]
q^{C}_{-j}						-0.003
						[-0.53]
CFS_{-j}					0.067	0.168
					[0.98]	[2.68]
$q^{\mathrm{SA}} \cdot CFS_{-j}$					0.277	0.465
					[2.84]	[3.37]
$q^{\mathrm{C}} \cdot CFS_{-j}$						-0.333
						[-1.93]
R-squared	0.261	0.261	0.263	0.264	0.102	0.103
Number of observations	104,417	104,417	104,417	104,417	18,248	18,248

Table VI
Industry Characteristics and Division Values: Industry Conditions

This table reports relative division values (RDVs), the associated bootstrapped p-values, and valuation ratios for conglomerate divisions and standalone firms in five classes ("Low" to "High") as well as the difference "High-Low". The average number of divisions in each class is also reported. Every year, we obtain industry-wide measures of industry conditions at the two-digit SIC level, and use those to group the industries into five classes. The measures are industry sales growth (Panel A) and the median analyst growth forecast for earnings-per-share (Panel B).

	Low		Med		High	High-Low
A. Sales growth						
RDV	-0.09	-0.15	-0.15	-0.23	-0.28	-0.19
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Division value	0.94	0.92	0.91	0.94	0.97	0.03
Standalone value	1.09	1.12	1.12	1.28	1.46	0.37
Avg. number of divisions	170	271	265	228	107	
B. Analyst growth forecast						
RDV	0.11	-0.11	-0.21	-0.24	-0.19	-0.30
p-value(RDV≤0)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Division value	1.27	0.84	0.86	0.89	0.97	-0.30
Standalone value	1.22	0.98	1.17	1.25	1.32	0.10
Avg. number of divisions	150	200	271	279	139	

Table VII
Exposure to Adverse Industry Conditions and Division Values

This table reports relative division values (RDVs), the associated bootstrapped *p*-values, and valuation ratios for conglomerate divisions and standalone firms. Divisions are separated into three groups: for conglomerates with at least one division affected by adverse industry conditions, we separately report valuations of these directly affected divisions as well as all remaining, indirectly affected divisions. For conglomerates that are unaffected by adverse industry conditions, we group all divisions. Adverse industry conditions are defined as two-digit SIC industries that fall in the lowest quintile of industry sales growth (Panel A) and the median analyst growth forecast for earnings-per-share (Panel B).

	Directly Affected Divisions	Indirectly Affected Divisions	Unaffected Conglomerates
A. Lowest sales growth quintile			
RDV	-0.06	-0.26	-0.21
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)
Division value	0.96	0.87	0.91
Standalone value	1.09	1.20	1.20
Avg. number of divisions	170	139	426
B. Lowest analyst growth forecast quintile			
RDV	0.15	-0.28	-0.24
p-value(RDV≤0)	(0.00)	(1.00)	(1.00)
Division value	1.30	0.83	0.86
Standalone value	1.22	1.19	1.19
Avg. number of divisions	150	115	446

Table VIII
Industry Characteristics and Division Values: Investment Intensity

This table reports relative division values (RDVs), the associated bootstrapped p-values, and valuation ratios for conglomerate divisions and standalone firms in five classes ("Low" to "High") as well as the difference "High-Low". The average number of divisions in each class is also reported. Every year, we obtain industry-wide measures of investment at the two-digit SIC level, and use those to group the industries into five classes. The measures are median capital expenditures relative to lagged assets (Panel A) and the broader measure of investment that also accounts for acquisitions and the sale of property, plant, and equipment (Panel B).

	Low		Med		High	High-Low
A. Capital expenditures						
RDV	-0.29	-0.31	-0.13	0.06	0.11	0.40
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)	(0.01)	(0.00)	(0.00)
Division value	0.70	0.83	0.85	1.14	1.42	0.72
Standalone value	1.19	1.26	0.99	1.08	1.41	0.21
Avg. number of divisions	100	312	299	170	136	
B. Investment						
RDV	-0.30	-0.26	-0.19	0.02	0.08	0.38
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)	(0.35)	(0.00)	(0.00)
Division value	0.72	0.80	0.87	1.02	1.62	0.89
Standalone value	1.35	1.14	1.09	0.99	1.66	0.31
Avg. number of divisions	86	301	306	184	136	

Table IX
Industry Characteristics and Division Values: Innovation

This table reports relative division values (RDVs), the associated bootstrapped *p*-values, and valuation ratios for conglomerate divisions and standalone firms in five classes ("Low" to "High") as well as the difference "High-Low". The average number of divisions in each class is also reported. Every year, we obtain industry-wide measures of innovation at the two-digit SIC level, and use those to group the industries into five classes. The measures for innovation are the median ratios of R&D expenditures to sales, as in Leary and Roberts (2010) (Panel A), and of patents to book value (Panel B).

	Low		Med		High	High-Low
A. R&D intensity						
RDV	-0.13	-0.02	-0.10	-0.11	-0.33	-0.20
p-value(RDV$\leq$0)	(1.00)	(0.84)	(1.00)	(1.00)	(1.00)	(1.00)
Division value	0.54	1.30	0.90	1.01	1.04	0.50
Standalone value	0.63	1.32	1.09	1.14	1.63	1.00
Avg. number of divisions	181	61	184	233	319	
B. Patent intensity						
RDV	0.44	-0.07	-0.09	-0.18	-0.29	-0.73
p-value(RDV$\leq$0)	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Division value	1.57	0.95	0.81	0.75	0.89	-0.68
Standalone value	1.16	1.14	0.96	0.97	1.32	0.16
Avg. number of divisions	117	157	201	281	259	

Table X
Industry Characteristics and Division Values: Competition

This table reports relative division values (RDVs), the associated bootstrapped p-values, and valuation ratios for conglomerate divisions and standalone firms in five classes ("Low" to "High") as well as the difference "High-Low". The average number of divisions in each class is also reported. Every year, we obtain industry-wide measures of competition at the two-digit SIC level, and use those to group the industries into five classes. The measures for competition are Herfindahl indices over market capitalization (Panel A) and total assets (Panel B), the number of firms (Panel C), and the median Li, Lundholm, and Minnis (2013) competition measure (Panel D).

	Low		Med		High	High-Low
A. Herfindahl over market equity						
RDV	-0.25	-0.24	-0.14	-0.06	0.07	0.32
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)	(1.00)	(0.42)	(0.00)
Division value	1.09	0.84	0.83	0.74	1.12	0.04
Standalone value	1.60	1.14	0.98	0.81	1.12	-0.48
Avg. number of divisions	362	273	218	137	40	
B. Herfindahl over assets						
RDV	-0.22	-0.17	-0.16	-0.11	-0.09	0.12
p-value(RDV≤0)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.03)
Division value	1.09	0.90	0.76	0.74	1.03	-0.06
Standalone value	1.52	1.13	0.91	0.83	1.16	-0.35
Avg. number of divisions	351	276	209	130	74	
C. Number of competing firms						
RDV	-0.01	-0.12	-0.15	-0.31	-0.33	-0.32
p-value(RDV≤0)	(0.74)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
Division value	0.78	0.66	1.35	1.12	1.07	0.29
Standalone value	0.79	0.75	1.65	1.75	1.67	0.89
Avg. number of divisions	221	250	235	171	165	
D. Li, Lundholm, and Minnis (2013) competition						
RDV	-0.03	0.02	-0.07	-0.21	-0.31	-0.28
p-value(RDV≤0)	(0.71)	(0.34)	(0.98)	(1.00)	(1.00)	(1.00)
Division value	1.57	0.99	0.89	0.97	1.20	-0.37
Standalone value	1.93	0.99	0.98	1.33	1.77	-0.16
Avg. number of divisions	78	127	174	233	218	

Table XI
Impact of Industry Deregulation on Division Values

This table reports the impact of industry deregulation on values of conglomerate divisions and standalone firms. The sample of deregulation events is from Table 3B of Harford (2005). After excluding events in the financial industry, events for which we have fewer than 25 conglomerate divisions, and events in industries that had deregulation events in the previous year, the sample comprises of 10 observations. See Appendix C for a detailed sample description. g^{C} and g^{SA} are, respectively, the growth rates in valuation ratios of conglomerate divisions and median standalone firms in the affected industry from the year prior to deregulation to the event year, and ΔRDV is the change in relative division values. The trimmed sample is obtained by excluding the smallest and the largest observation in the sample. Also reported are standard errors and bootstrapped p-values.

	g^{C}	g^{SA}	$g^{\mathrm{C}} - g^{\mathrm{SA}}$	ΔRDV
Mean	-0.078	0.001	-0.078	-0.102
Fraction negative	0.80	0.60	0.80	0.80
Std. Error	(0.05)	(0.08)	(0.05)	(0.05)
p-value ($\leq$0)	(0.87)	(0.38)	(0.88)	(0.94)
Trimmed Mean	-0.072	0.020	-0.079	-0.097
Fraction negative	0.88	0.63	0.88	0.88
Std. Error	(0.04)	(0.05)	(0.05)	(0.05)
p-value ($\leq$ 0)	(0.94)	(0.39)	(0.90)	(0.95)

Table XII
Valuations of Core and Peripheral Divisions

This table reports relative division values (RDVs), the associated bootstrapped p-values, and valuation ratios for conglomerate divisions and standalone firms that are central ("core") or peripheral to the conglomerate, as well as the difference. The average number of divisions in each class is also reported. Core divisions are ones that have the same four-digit SIC code as Compustat reports for the conglomerate (Panel A), or the divisions with the largest assets (Panel B) or sales (Panel C) within the conglomerate. The standalone firm valuations are the median valuation of all standalone firms whose size falls within the support of the size distribution of the conglomerate divisions in the respective class.

	Core	Peripheral	Difference
A. Compustat 4-digit SIC code			
RDV	-0.23	-0.11	0.11
p-value(RDV≤0)	(1.00)	(1.00)	(0.05)
Division value (DV)	0.97	1.15	0.17
p-value(DV≤0)	(0.00)	(0.00)	(0.04)
Standalone value	1.32	1.28	-0.04
Avg. number of divisions	282	282	
B. Largest division by assets			
RDV	-0.23	-0.14	0.09
p-value(RDV≤0)	(1.00)	(1.00)	(0.00)
Division value (DV)	0.87	0.97	0.11
p-value(DV≤0)	(0.00)	(0.00)	(0.00)
Standalone value	1.16	1.16	-0.01
Avg. number of divisions	531	531	
C. Largest division by sales			
RDV	-0.21	-0.17	0.03
p-value(RDV≤0)	(1.00)	(1.00)	(0.14)
Division value (DV)	0.88	0.96	0.08
p-value(DV≤0)	(0.00)	(0.00)	(0.03)
Standalone value	1.16	1.17	0.00
Avg. number of divisions	531	531	