Conglomerate Investment, Skewness, and the CEO Long Shot Bias

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Abstract

We show that segment-level capital expenditure in conglomerates is increasing in the expected skewness of segment returns. Conglomerates with a high-skewness segment are valued at a substantial discount of up to 15%, which indicates overinvestment that is detrimental to shareholder wealth. Conglomerates invest significantly more in these segments than matched stand-alones. The findings are robust to industry, firm, and segment fixed effects, and are not driven by simple valuation mistakes, investment opportunities, or agency problems. Using a proxy based on geographical variation in gambling norms, we show that the skewness-investment relation is particularly pronounced when CEOs are likely to find gambling attractive. The results are the first evidence to show that skewness is related to capital budgeting and the first to suggest that biased CEOs who try to pick winners are betting on long shots, instead.

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1. Introduction

Capital investment decisions within conglomerates are of first order economic importance. Over the last two decades, total capital expenditure of conglomerate firms has averaged \$142 billion per year for all firms in Compustat. Central in allocating capital to the conglomerate's various divisions are CEOs. They have "total and unconditional control rights" and can "unilaterally decide" what to do with a divisions' physical assets (Stein (2003)). Almost 40% of CEOs of US CEOs claim that they make capital allocation decisions with very little or no input from others according to a survey by Graham, Harvey, and Puri (2010).

While efficiently allocating capital is important, and while CEOs are critical in the process, making correct capital budgeting decisions is a difficult task. This is so because even the best valuation tools often have to rely on assumptions that are subjective. For almost any investment project, two equally sophisticated individuals can obtain substantially different NPV estimates. As a simple example, suppose that the cash flow of a project is \$1 this year. The appropriate discount rate is 5%. Assuming a perpetual growth rate of 2% leads to a project value of \$33.3. Using an equally defensible 3%, instead, one obtains a value estimate of \$50.0, which is 50.0% higher. Figure 1 presents a more realistic example from a leading textbook on valuation. It shows the results from simulating project NPV. Necessary inputs include probability distributions of future sales growth, margins, ability to expand production, several cost overrun factors, as well as the correlations between these random variables. As in the perpetuity example, the NPV estimate is very sensitive to the underlying assumptions, which, in turn, are extremely hard to get right. "Valuation uncertainty" is large.

Valuation uncertainty can lead to substantially distorted capital budgets through a number of mechanisms. We identify three of them that are relevant for our study. First, if valuation uncertainty is large it is difficult to identify the right project. Hence, even CEOs who want to maximize value might end up misallocating some capital by mistake. Second, CEOs or division managers can strategically use valuation uncertainty to extract private benefits when agency problems are present. Third, behavioral biases of CEOs can systematically distort capital allocation because valuation uncertainty makes the decision context informationally sparse and CEOs rely more on intuitive reasoning. Consistent with such a role for behavioral factors, more than 50% of CEOs surveyed in Graham, Harvey, and Puri (2010) mention "gut feel" as an important or very important factor in their capital allocation decisions.

The first two channels have been discussed widely in the literature (see e.g., Stein (2003) for a survey). In contrast, except for the very few papers we cite below, there is little work analyzing the impact of managerial biases on capital budgeting. Our paper provides new evidence suggesting that behavioral biases of top decision makers can lead to distorted capital budgets that do not maximize shareholder wealth. Specifically, we highlight the implications of a powerful behavioral phenomenon which we label the "CEO long shot bias". The CEO long shot bias is shorthand for a cognitive bias that induces a preference for high expected skewness and large but low-probability upside potential. One prominent potential source of the bias is prospect theory's probability weighting feature, but as we discuss in greater detail below, there may also be other deep drivers. The crucial implication of the CEO long shot bias is that it leads conglomerates to systematically overinvest in segments with high expected skewness, which destroys firm value. The intuition can be summarized easily: biased CEOs try to pick winners but, because valuation uncertainty is generally high, they end up betting on long shots.

To fix ideas, consider the example of a hypothetical conglomerate with two divisions, A and B. Both divisions have existing projects in place. The CEO oversees a fixed investment budget of $I = 5$ for new projects that he can either allocate to division A or to division B. Division A proposes the following project:

$$[(2, 0.4); (8, 0.6)]$$

This project generates a present value of cash flows before investment of 2 in the low state, which occurs with a probability of 0.4, and 8 in the high state with probability 0.6. Division B proposes a project with a more skewed payoff distribution.

$$[(2, 0.9); (30, 0.1)]$$

This project yields 2 in the low state, which has a probability of 0.9. There is a 10% chance, however, that project B is a major success and the value before investment is then 30. Based on these numbers, because the expected NPV of Project A is 0.6, and the expected NPV of project B is –0.2, the CEO should allocate the budget to project A. The key finding in our paper is that a substantial fraction of CEOs in conglomerates nevertheless prefer long shot project B to the safer project A.

In the first part of the paper, we show that capital expenditure is significantly higher for divisions with projects that are more likely to have higher skewness (project B in our example). Our sample consists of all U.S. conglomerates with sufficient data from 1990 to 2009 and we use a measure of expected segment skewness developed by Zhang (2006) and Green and Hwang (2012). Increasing segment skewness by one standard deviation leads to a 0.45 percentage point increase relative to an average capital investment to asset ratio of 7.4%. For small segments, for which the impact of reallocating capital budgets is larger, this effect further magnifies to 1 percentage point. This pattern is robust to a battery of controls including firm and segment fixed effects. It is also robust to using changes instead of levels. These tests establish a positive relation between expected skewness and investment in conglomerates and show that this skewness-investment relation is economically large.

Looking at value implications, we find that conglomerate firms with skewed segments are valued by the market at significant discounts of up to 15%. These tests use the method of Berger and Ofek (1995), adjusted to controlling for endogeneity of the diversification decision with fixed effects, instrumental variables techniques, and selection models, as in Campa and Kedia (2002). As in our simple motivating example above, this set of results suggests that conglomerates overinvest into segments with high expected skewness and that this investment behavior is detrimental to shareholder wealth.

The data point to a specific role for the internal capital market mechanism in conglomerates in these investment patterns. When we match conglomerate segments to comparable stand-alone firms, we find that investment in conglomerates is significantly higher even though we control for potentially greater debt capacity. Looking only at stand-alones, there is no skewness-investment relation once we control for industry specific effects. This suggests that skewness is not simply proxying for investment opportunities over and above the standard control variables.

These empirical patterns are potentially consistent with the three channels outlined above. First, the project with more skewed returns (project B) might be harder to value and therefore more prone to simple valuation errors. Agency theory delivers a second possible explanation. Under this view, CEOs can strategically exploit valuation uncertainty to tilt capital budgets towards an allocation that maximizes private benefits (e.g., Scharfstein and Stein (2000), Rajan, Servaes, and Zingales (2000)). Similarly, career concerns might lead CEOs to choose project B because succeeding in it would be a strong signal of skill. Our analysis shows that valuation mistakes or agency problems, while being important in many areas of conglomerate investment, cannot easily explain the skewness-investment relation we document.

Our preferred explanation is that managers subject to the long shot bias choose project B *because* it offers a larger upside potential and a smaller winning probability than project A. For example, if the long shot bias is due to prospect theory's probability weighting feature, a CEO would choose project B because he evaluates the winning probability $p = 0.1$ for project B *as if* it were a probability of 0.15. This leads to an estimated NPV of 1.2, which is higher than the NPV of project A. Under this scenario, a CEO would choose project B even if there was no disagreement about the true probability 0.1. Of course, in most relevant cases, it will be practically impossible to tell if there is a 10% or 15% chance that the project will be a home run, so there is every possibility for the CEO to ex post rationalize any decision close to his, potentially subconscious, preference. Another plausible driver of the long shot bias is anticipation utility: CEOs go for project B because it feels especially good to win big (e.g., Brunnermeier and Parker (2005)).

Valuation uncertainty greatly amplifies the potential for the long shot bias to affect capital allocation because any decision on which project to fund will have to rely at least partly on intuitive reasoning. Kahneman (2011) argues that a standard procedure of our cognitive apparatus is substituting a difficult question ("what is the probability that the project will be a home run?"), with a simpler question ("can I easily think of instances where similar projects were home runs?"). Because we construct our skewness measure based on outcomes of similar projects in the recent past, high expected skewness will by definition be associated with instances of recent successes that will come to mind easily. Substitution and the availability heuristic would then lead to particularly optimistic forecasts for positively skewed projects. All three deeper drivers of the long shot bias – probability weighting, anticipation utility, or the availability heuristic – lead to the same outcome: the long shot project B is chosen and this destroys shareholder wealth. Because our aim in this paper is to show that the long shot bias has measurable and economically substantial effects on the efficiency of capital budgets, we remain agnostic about which of the potential deeper sources is ultimately driving the bias.

A key difference to the agency models above is that there, the CEO knows he is not maximizing firm value. He consciously trades-off private benefits for shareholder value. By contrast, a CEO subject to the long shot bias may actually try to maximize shareholder value, but fail because the bias is subconscious ("gut feeling").

We provide a direct test of the CEO long shot bias hypothesis, by exploiting exogenous variation in the CEO's propensity to gamble. Specifically, we use CPRATIO, a variable developed by Kumar, Page, and Spalt (2011), that captures gambling propensity of decision makers in a geographical area. CPRATIO is based on local religious beliefs and associated gambling-norms, so it is exogenous with respect to capital allocation decisions. When we split our sample according to the CPRATIO measure, we find that the skewness effects are concentrated where gambling propensity is high. We argue that this test is particularly informative because it raises the bar for any alternative explanation of our results: any candidate variable must not only be positively correlated with the propensity to invest in skewed project B. It must also be positively correlated with CPRATIO, i.e., the fraction of Catholics in the county of the company headquarters. As an example, misaligned risk-taking incentives from inefficient contracting, perhaps because CEOs have captured the pay setting process (e.g., Bebchuk and Fried (2004)), does not easily explain our specific set of results as it is not obvious why inefficient contracting should be more of a problem in Catholic regions. A similar argument holds for career concerns.

Additional evidence supports the hypothesis that the skewness-investment relation is induced by CEOs who are attracted to long shots. For example, using data on regional lottery ticket sales, we find that investment in skewed segments is high when people around the headquarter buy more lottery tickets, i.e., when the local gambling propensity increases. The skewness-investment relation is stronger for younger CEOs and for CEOs who are powerful in their organization. In sum, we conclude that our evidence on the skewness-investment relation is most consistent with distorted capital budgets due to the CEO long shot bias.

Our novel findings contribute to a branch of behavioral corporate finance which Baker and Wurgler (2011) label "irrational manager-rational markets" approach. Related papers include Malmendier and Tate (2005), who analyze investment-Q-sensitivity for overconfident managers, and Kruger, Landier, and Thesmar (2011), who study capital allocations when firms use the same discount rate across divisions. While we look at a different bias, we share with those papers the general notion that the conglomerate structure, and the special discretion it confers to CEOs, to some degree allows executives to make suboptimal decisions for shareholders. To the best of our knowledge, our paper is the first to document that skewness is related to capital allocation and the first to suggest that CEO gambling attitudes can contribute to seriously distorted capital budgets.

Our focus on the long shot bias is grounded in a large body of prior work. It is one of the most well-established facts in decision-making and has a long history going back at least to Friedman and Savage (1948) and Markowitz (1952). We borrow the term from the favorite-long shot bias in horse betting. On race tracks, long shots are heavily overbet. In this context, Golec and Tamarkin (1998) document that the preference for long shots is due to skewness as opposed to risk, and Snowberg and Wolfers (2010) show that the skewness preference is most likely induced by probability distortions as in prospect theory. In more general decision-making settings, Kahneman and Tversky (1979) and Tversky and Kahneman (1992) establish that subjective valuations of a gamble increases in its skewness. For small probabilities of large gains, certainty equivalents frequently exceed expected values and Kachelmeier and Shehata (1992) provide field evidence to show that this behavior is also present when stakes are very large. Barberis and Huang (2008) apply the idea of probability weighting in an asset pricing context. Our paper is among the first to apply these ideas in the corporate domain.

Section 2 presents the data. Section 3 documents the skewness-investment relation and its value implications. We present results on our preferred explanation, the CEO long shot bias, in Section 4 and discuss potential alternative explanations in Section 5. Section 6 concludes.

2. Data

2.1 Compustat Data

Our sample is based on the Compustat Segment files, covering the 20-year period from 1990 to 2009. We only include business segments and operating segments that are organized divisionally. In the following, segment and division have the same meaning and we use the terms interchangeably. We retrieve information on assets, sales, capital expenditures, operating profits, depreciation, and the 4-digit SIC code for each segment. We define a segment's industry based on its primary SIC code. If it is not available we use the primary SIC code for business segments. If both variables are missing we drop the observation. All duplicates of segment-year observations are deleted and we only keep the first observation from the original 10-K report. In the next step we merge the segment data with firm-level data from the Compustat Fundamentals Annual database. In order to ensure consistency between both databases we remove all observations where the sum of segment sales does not fall within 5% of total firm sales. We also drop all observations where sales or total assets are missing, zero, or negative. All firms which are in the Compustat Fundamentals Annual database but not in the segment data set are treated as single segment (stand-alone) firms. Finally we match the 4-digit SIC code of all segments and stand-alone firms with the corresponding Fama-French 48 (FF48) industry and aggregate within each firm all segments in the same FF48-industry into one division. All firms active only in one FF48-industry are also treated as stand-alone firms. Conglomerate firms are firms operating in more than one FF48-industry. We drop divisions and firms with (i) missing sales or asset data, (ii) assets less than $1 million, (iii) anomalous accounting data (zero or negative depreciation, capital expenditures less than zero or greater than assets, negative book equity, cash flow over assets less than -1), and (iv) missing or zero market capitalization.

Table 1 shows our final sample separately for segments, conglomerates, and stand-alone firms.

2.2 Skewness Measure

Our main explanatory variable is the expected skewness of segment returns, $Skew$. Since expected skewness on the segment level is not observable because segments do not have traded stock, we follow Zhang (2006) and Green and Hwang (2012) in using an industry-level approximation based on stand-alone firms. Specifically, we construct:

$$Skew_{i,t} = \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{(P_{99} - P_1)} \tag{1}$$

where P_j is the j-th percentile of the log return distribution pooled across all firms within the same FF48-industry of division i over its preceding fiscal year.

The industry-level skewness proxy is ideal for our setting for a number of reasons. First, it is a plausible and easy to obtain proxy of expected skewness. Second, as Green and Hwang (2012) show, it is highly correlated with ex post measures of return skewness. Third, on a cognitive level, salience and the availability heuristic (e.g., Kahneman (2011)) supports the idea that looking at skewness of returns in an industry in the last year has predictive content for managerial investment decisions. Extreme returns in an industry make this industry salient to CEOs and they will see a project in a more positive light if instances of recent successes of similar projects come to mind easily. Since, by construction, the industry-level skewness measure is high whenever salience is high, it is ideal to capture these heuristic-based effects. Finally, an attractive feature of the measure is that it highlights the importance of the tails of the distribution by focusing on extreme return percentiles. It is these tails that are attractive to individuals with a preference for long-shot bets (e.g., Barberis and Huang (2008)). Bali, Cakici, and Whitelaw (2011) even show that it might be more appropriate to focus only on the largest positive returns in the recent past, i.e. the extreme right tail of the distribution, rather than on overall skewness to capture what is attractive to individuals who like long-shot bets.

We show in our robustness checks that our results are robust to sensible variations of the skewness measure.

2.3 Additional Variables and Data Sources

In addition to our main variable *Skew*, we control for the standard variables used in the literature. We follow Shin and Stulz (1998) and control for divisional and firm cash flows, defined as sum of operating profits and depreciation scaled by total assets. Additionally we control for the median Tobin's q in a division's FF48-industry and the median Tobin's Q in the conglomerate's main FF48-industry. The median is calculated across all stand-alone firms that operate in the same FF48-industry and Tobin's Q is defined following Ozbas and Scharfstein (2010) as $MVA/(0.9 * BVA + 0.1 * MVA)$, where BVA is the book value of assets and MVA is the market value of assets (common equity plus the book value of assets minus the book value of common equity and balance sheet deferred taxes). It is bounded above at 10 to reduce the effect of potential measurement error in the book value of assets. Following Kruger, Landier, and Thesmar (2011) we also control for size of the firm, defined as the log of sales, age of the firm, defined as log of the current year plus one minus the year in which the firm first appeared in the Compustat database, and the focus of the firm, defined as the ratio of the core (i.e., largest) division's sales and the firm's total sales. In some tests we additionally include sales growth, R&D expenditures over assets, and the division's industry asset beta as controls. We winsorize all continuous variables at the 1% and 99% level.

We use religious affiliation data obtained from the "Churches and Church Membership" files from the American Religion Data Archive (ARDA), state-level lottery sales data from the North American Association of State and Provincial Lotteries (NASPL), county-level demographic data from the U.S. Census, the Chicago Fed national activity index (CFNAI), CEO age, compensation, and ownership data from ExecuComp, and the GIM-index data from Andrew Metrick's website. We document all variables used in our analysis and their definitions in Table A.1 in the Appendix.

3. The Skewness-Investment Relation

3.1 Baseline Results

We start our analysis by documenting that divisional investment inside conglomerates is positively related to the skewness properties of the division. We regress capital expenditure scaled by total segment assets on segment skewness and controls. Our strategy is to be conservative and to follow the prior literature closely on the specifications and control variables we use. The main variables of interest are division skewness and the interaction of division skewness with division size. We conjecture that it is much easier for a firm to substantially alter the investment budget of a small division and therefore include the interaction term. Since we are controlling for total firm size, the interaction captures the impact of the relative size of the segment. Division size is measured by segment sales and the interaction term is written as to be larger for smaller segments. Our measure of division skewness is the industry-level measure of skewness described in Section 2. We run OLS regressions and use standard errors that allow for clustering at the firm level.

Table 2 presents our baseline results. Across all models, we find that divisions with positively skewed expected future returns invest more. As shown by the interaction term, this effect becomes stronger for smaller segments. The results are robust to the standard control variables used in the literature. Specifically, we control for segment cash flow and segment investment opportunities (proxied for by Tobin's Q). As expected, segment investment is higher when the segment has higher cash flow and better investment opportunities. We also control for investment opportunities of the largest segment by sales (which we call the core segment), without any effect on our coefficients of interest.

Segment investment increases in firm cash flow. As we already control for segment cash flow, this indicates that internal capital markets are active. We control for firm size and firm focus but both variables turn out to be insignificant once we include industry dummies. Lastly, we include firm age and find that older firms have lower investment levels. We include industry dummies for both segment and firm level along with year dummies. Overall, our main result is that segment skewness is positively related to investment and that the effect is not captured by a set of standard control variables.

The effect of segment skewness on investment is economically sizeable. The estimates in specification (4) in Table 2 indicate, for example, that a one standard deviation increase in skewness (0.03) increases segment investment by 0.45 percentage points ($= [17.811 + 3.139 \times (-0.94)] \times 0.03$) or 6.1% of investment for the average segment. In dollar terms, the average segment would increase capital expenditure by \$4.5 million from \$74.4 million to \$78.9 million. The impact of segment size on the skewness effect is also quite striking. The standard deviation of the interaction term is 0.18, so the estimates indicate that segment investment increases by an additional 0.56 percentage points ($= 3.139 \times 0.18$) when the interaction term changes by one standard deviation. Hence, the effect of skewness is twice as large when the segment is smaller. Another way to think about the magnitude is that the difference in investment between a small skewed segment and a large non-skewed segment is about 1 percentage point ($= 0.45 + 0.56$). Relative to a mean investment of 7.39% this is economically large.

3.2 The Skewness-Investment Relation and Unobservables

Table 2 shows that investment increases in segment skewness and that this effect can neither be explained by standard observables used in the literature, nor by technological or other stable differences on the industry level. A potential concern could be that there are unobservables at either the firm or the division level that are driving our results. Before addressing this concern, we note that it is not immediately obvious what these unobservables should be, given that we need not only a positive relationship between the omitted variable, investment, and skewness, but also and a negative relationship between this variable and segment size.

Table 3 shows that unobservables are unlikely to be driving our results. In specification (1), we regress the year-to-year change of division investment on the year-to-year change in skewness and the control variables. This model tests if investment responds to changes in skewness. It also wipes out all unobservable time-invariant factors on the segment level. The results indicate that firms increase their investment following an increase in skewness. That is, CEOs invest more in long shots when recent successes in similar projects become more salient. We also run fixed effects regressions. First, we include conglomerate fixed effects, which may capture, for example, time-invariant differences in the ability of top management to identify profitable new technology ventures, which might be both small in size and high in skewness. Second, we control for segment fixed effects, which, not surprisingly, leads to similar results than the change regressions. All results remain qualitatively unaffected. We conclude that higher investment in segments with high expected skewness cannot be explained by unobservable time-invariant heterogeneity on the firm or division level.

Another potential concern might be that there are unobservable time-varying factors that drive the skewness-investment relation. We use two approaches from the existing literature to investigate this possibility. First, we follow a similar approach as in Lamont (1997) and control for common shocks to investment in an industry in a given year, for example technology or regulatory shocks. Specifically, we subtract the mean asset weighted investment across all stand-alone companies in the same FF48-industry from the division investment variable used in Table 2. This industry-adjusted investment variable is thus capturing variation in investment levels that are not related to distortions in conglomerate capital allocation. (Implicitly, this specification compares conglomerate segments to stand alone companies; an issue we investigate further in Section 3.4.) Column (4) documents that the skewness-investment relation is not driven by common industry shocks. In fact, our results get even stronger by eliminating this variation.

The second approach follows Rajan, Servaes, and Zingales (2000) and accounts for the fact that conglomerates might be able to raise more cash than stand-alones. Therefore, conglomerates might invest more in *all* divisions. To account for this, we adjust the industry-adjusted segment investment by subtracting the asset weighted average industry-adjusted segment investment across all the segments of the conglomerate firm. We call the resulting variable the firm-industry-adjusted investment measure. The final specification in Table 3 shows that the documented relation between skewness and investment is not spuriously induced by a (time-varying) tendency of conglomerates to invest more across the board.

These tests show that the skewness-investment relation is robust to several alternative variants of running our main regressions. In particular, Table 3 shows that it is unlikely to be driven by obvious unobservables.

3.3 Robustness

Our results are robust to altering the calculation of the industry-level skewness measure (see Table 4). We propose three alternatives. First, we use the 5th and 95th percentile instead of the 1st and 99th percentile of the log return distribution in calculating the measure. Second, we use two years of return data. Third, we use the MAX measure proposed in Bali, Cakici, and Whitelaw (2011), which focuses only on the maximum returns in an industry in the last year. All results continue to hold using these versions of the skewness measure. The results for the MAX measure also suggest that seeking upside potential, rather than a desire to avoid losses, drives the positive skewness-investment relationship.

We perform a range of additional tests. First, we control for the mean stock return across stocks in a given FF48-industry and find that the skewness (the third moment) is not simply a proxy for average returns (the first moment). We next show that our results are not driven by overinvestment in new economy firms. Excluding tech-related firms (SIC codes 3570 to 3579, 3661, 3674, 5045, 5961, or 7370 to 7379) does not change our findings. We are also not capturing effects from tiny firms that might bias our sample because our investment measure is in percent. Dropping all segments with assets below \$10 million does not alter our results. In another set of tests, we show that the vega of the CEO pay package – the value change of the CEO option package for a change in the riskiness of the firm – and overconfidence does not explain our results (see Appendix A.1 for details on how we construct these two variables). We control for CEO age and tenure in these tests. Although we lose almost 75% of our sample because the ExecuComp data needed to construct both the vega and the overconfidence measure is only available for this subset, we get clear results showing that the skewness-investment relation is neither induced by risk-taking incentives from pay packages, nor capturing effects related to overconfidence.

Next, we consider a framing issue. Narrow framing for capital budgeting problems is natural because of the process in which capital budgets are set up. Frequently, initial budgets are compiled on the division level before top management decides on how to split the available resources between the divisions. Often, budgeting comes with substantial lobbying of divisional managers. All this establishes the division level as natural unit of account and thus makes narrow framing very likely. Consistent with this view, our results are not affected when we control for the overall level of firm skewness (the "broad" frame), which we compute by a value-weighted average of segment skewness in the conglomerate.

Kruger, Landier, and Thesmar (2011) propose that firms overinvest into high beta segments because they use one overall beta to evaluate investment projects. To rule out that our effects obtain because skewness is correlated with betas, we include segment betas computed as in Kruger, Landier, and Thesmar (2011). All our results are unaffected, which shows that we are capturing a different effect. The previous robustness check is also valuable from another angle. Since betas are a measure of systematic risk, the tests show that it is not risk *per se* that is driving our results. Rather, it is the tails of the distributions, which our skewness measure is designed to capture, that have an impact on corporate allocation decisions. Lastly, we find that our effect is present when we split our sample in decades, so it is not specific to any time-period within our sample. Overall, we conclude that our results are robust to a number of plausible alterations of our baseline setup.

3.4 Comparing Conglomerates to Stand-Alone Firms

The evidence so far shows that conglomerates invest more into skewed segments than can be explained by standard determinants of investment levels. An alternative test to show that investment in skewed segments is particularly high is to compare conglomerate segments with otherwise comparable stand-alone firms.

To implement this test, we follow the matching procedure proposed in Ozbas and Scharfstein (2010). Specifically, we match a conglomerate segments to a stand-alone firm by industry, year, size, and firm age. Whenever there are multiple possible matches, we randomly assign a match based on the firm name. We then run:

$$\Delta Investment = \alpha + \beta_1 Skew_{DIV} + \beta_2 Q_{DIV} + \beta_3 \times \Delta CashFlow + \epsilon, \qquad (2)$$

that is we relate the difference in investment levels between division and stand-alone, denoted by $\Delta Investment$, to the skewness of the industry. Our prediction is that β_1 is positive, which indicates that the difference in investment levels between divisions and stand-alones increases with industry skewness. The constant in the regression controls for average differences in investment across divisions and matched firms, which might result, for example, from greater external debt-capacity due to the conglomerate structure. We also include Tobin's Q and the difference in cash flow levels because these variables have been shown to predict differences in investment levels by Ozbas and Scharfstein (2010). Hence, we want to make sure that our skewness effect is indeed unrelated to these known determinants.

Table 5 presents results. Looking at the top panel, we find that the coefficient on skewness is positive and significant, which indicates that the higher investment levels of conglomerate segments is particularly pronounced for segments in industry with high expected skewness. This is true for four different procedures to find a match, including matches by (i) industry and year, (ii) industry, year and size (iii) industry, year, and size, provided that the size of the potential match is within 10% of the segment size, and (iv) industry, year, size, and firm age. Since we control for Q and cash flow differences, the results cannot be explained by differences in investment opportunities, or cash flow available at the segment level.

These patterns are consistent with overinvestment of conglomerates in divisions with a lot of expected skewness; a practice that could be facilitated by the ability of management to redistribute capital across divisions. The evidence thus compliments our regression evidence using industry-adjusted variables in Table 3. A possible alternative view would hold that stand-alone firms underinvest in these industries. While we note that it does not seem obvious why this would be the case, given that we are already controlling for difference in access to capital, we propose a simple test to rule out this alternative explanation. Our argument is based on relative segment size. If the patterns are due to overinvestment in conglomerates, then the effects should be more pronounced for relatively small segments, because it is easier for firms to meaningfully alter investment budgets through reallocating resources across divisions if the segment is small and the rest of the firm – and therefore the resources to be reallocated – are large. By contrast, if effects are due to underinvestment in stand-alones, the *relative* size of the matched segment should not matter.

The bottom two panels of Table 5 show that the effects are concentrated among matches of single-segment firms with segments that are relatively small within their conglomerate. Across all matching strategies, the coefficients are twice as large as in the baseline case and the already high statistical significance further increases. The effects are not present when we look at the subset of relatively large segments. Note that the constant in these regressions picks up all stable differences across conglomerates and stand-alones. So even if there were differences in access to external funding across small and large segments in absolute terms, and even if the relative size match would not completely eliminate the relation to absolute size, such differences cannot easily explain why we see larger investment differences, because those would be captured by the constant.

Overall, the evidence in this section suggests that conglomerate firms use resources from internal capital markets to overinvest in small segments with high expected skewness.

3.5 Value Implications

The above results are consistent with conglomerate firms inefficiently channeling internal resources to segments with high expected skewness. If this channel is indeed operating, we would expect that the inefficiency is reflected in the value of multi-segment firms.

To test this formally, we augment standard diversification discount regressions with a term measuring the incremental discount for conglomerates with skewed segments. Following Berger and Ofek (1995) we compute a measure of excess value, defined as the log difference between market value and imputed value of the conglomerate. Imputed value of a conglomerate is the sum of the individual segment values estimated by using FF48-industry sales multipliers. We then regress this excess value on a dummy that is one for conglomerates and a large set of control variables used in Campa and Kedia (2002). To measure the impact of segment skewness on conglomerate value, we add a dummy variable, *Skewed*, that is one if the conglomerate has a division operating in an industry with above median expected skewness, which is outside the conglomerate's major FF12-industry. The latter condition allows us to focus on smaller segments, which is where we expect stronger effects. Alternatively we use the number of segments with above median skewness in the conglomerate instead of *Skewed*.

Table 6, Panel A presents results for the *Skewed* variable. We first run standard OLS regressions. Consistent with the existing literature on the diversification discount we find in Panel A, that conglomerates trade on average at a discount of about 9% to 11%. More interestingly, the significant negative coefficient on *Skewed* indicates that conglomerates that have at least one non-core division operating in an industry with high expected skewness trades at a discount that is another 40% to 50% larger. Hence, such multi-segment firms trade at a discount relative to other multi-segment firms without skewed segments, and relative to otherwise similar stand-alone firms. This is exactly what we would expect to see if inefficient internal capital allocation was driving overinvestment in skewed segments.

A common concern with this type of regressions is endogeneity because the decision to diversify might itself be endogenous. Note first that this may be irrelevant for our finding that conglomerates with skewed segments trade lower than other conglomerates since the endogeneity-induced bias – if it exists – would affect both variables, *Conglomerate* and *Skewed*, in the same way. To deal with this endogeneity problem more formally, we follow Campa and Kedia (2002) and add firm fixed effects to our regressions. If the decision to diversify is driven mainly by time-invariant factors on the firm level, then the fixed effects will eliminate the source of endogeneity. As shown in columns (3) and (4) of Table 7, including the fixed effects does not alter our main conclusions. Both, the diversification discount and the incremental discount due to the presence of a skewed on-core segment are somewhat attenuated but remain statistically and economically significant. In particular, we continue to find a sizeable detrimental effect on firm value from having a skewed segment of 1.8 to 2.3 percentage points, or 23% to 17% relative to other conglomerates.

Following the standard method described in Campa and Kedia (2002) we also use instrumental variables techniques and the Heckman selection model to rule out that endogeneity of the diversification decision is not contaminating our inferences. An instrument is valid if the exclusion restriction is satisfied, meaning that it is correlated with the decision to diversify (the first stage), but uncorrelated with the error term in the second stage. Campa and Kedia (2002) show that the fraction of firms in an industry that are diversified meets these conditions and is therefore a valid instrument. Following these authors and Kuppuswamy and Villalonga (2010) we therefore use it in our tests as well.

An additional feature of our setting is that if the diversification dummy is endogenous, then, since *Skewed* can only take the value of one for conglomerates, it is necessarily correlated with the diversification dummy and hence also endogenous. To the extent that *Skewed* is itself not endogenous, we can legitimately instrument it with the interaction of the instrument for the diversification dummy and *Skewed* to solve the endogeneity problem (Angrist and Pischke (2008), Chapter 4.6.2). To show the strength of our instruments, we report p-values for the Angrist and Pischke (2008) F-test for weak instruments.

Consistent with the diversification discount literature, we find that using IV and Selection methods affects the estimated of the diversification discount dummy (*Conglomerate*) substantially. Important in our setting is the coefficient on *Skewed*. The results in Table 6 show that controlling for endogeneity reinforces our previous results that conglomerates with a segment operating in a high skewness industry are valued at a discount. Across specifications (5) to (8), this discount relative to stand-alone firms is between 8% to 12%, which is economically clearly large. The difference to stand-alones is highly significant statistically. So is the difference to conglomerates without skewed segments. The Angrist-Pischke F-test suggests that weak instruments are not a concern.

Panels B shows that results are very similar when we use the number of segments with above median skewness as an alternative indicator for conglomerates with skewed segments where investment distortions are likely to be acute. Overall, the results in this sections are consistent with the hypothesis that overinvestment in skewed segments is detrimental to shareholder wealth.

4. Investment and the CEO Long Shot Bias

In this section, we present evidence for our preferred explanation for the skewness-investment relation documented above. Our preferred explanation is that CEOs subject to the long shot bias overinvest in projects with high expected skewness, such as project B in the example in the introduction. This will adversely affect shareholder wealth, because the skewed project is favored over a non-skewed project even if it has lower, and on the margin negative, NPV. We discuss potential alternative explanations in Section 5.

4.1 Evidence from a Geographical Gambling Proxy

A clean test of the hypothesis that the skewness-investment relation documented in the previous section is driven by a long shot bias of CEOs would exploit exogenous variation in the intensity of the bias, and then show that the investment in skewed segments is most pronounced, where the bias is strongest. The aim of this section is to provide such a test. We draw on recent work by Kumar, Page, and Spalt (2011) to identify exogenous variation in how much CEOs like long shots. Specifically, those authors propose using CPRATIO as a variable that captures gambling propensity of decision makers in a geographical area. CPRATIO is the ratio of Catholics to Protestants as a percentage of the total population in a county. This measure is motivated by the observation that Catholic teachings are more lenient towards gambling than Protestant teachings and that religious background, specifically the difference between Catholics and Protestants, is well-established as a key predictor of gambling behavior in the empirical gambling literature (e.g., Berry and Berry (1990), Martin and Yandle (1990), Ellison and Nybroten (1999), Diaz (2000), and Hoffman (2000)). Kumar, Page, and Spalt (2011) show that decision makers in regions with higher CPRATIO are more likely to take long shot bets in different contexts, including buying lottery tickets, stock market investment, and corporate decisions. Benjamin, Choi, and Fisher (2012) provide experimental support for the CPRATIO measure.

Our empirical strategy is to assign each conglomerate to a US county by headquarter – since this is where the CEO is – and then to assign to each firm the CPRATIO of this county. The key identifying assumption we make is that decision-making of CEOs is not orthogonal the religion-induced local gambling norm. For example, decisions of a manager in Salt Lake City would be influenced at least to some degree by the local Mormon culture (even if the manager is not a Mormon). We then re-run our baseline regressions for the subsample of high and low CPRATIO firms defined as firms located in counties with above median CPRATIO in a year. We follow Kumar, Page, and Spalt (2011) in constructing the variable and refer the reader to their paper for details.

Table 7 presents results which are consistent with the long shot hypothesis. We find that in low CPRATIO counties, which is where gambling and skewness in returns are less attractive, our effects become severely attenuated and, although they keep the right sign, become insignificant. By contrast, effects in high CPRATIO counties are very large. Coefficients are almost 5 times as large and highly statistically significant. Wald tests indicate that the coefficients on both the baseline skewness effect, as well as the interaction effect are different across the subsamples.

Since we are including industry fixed effects for each division in our regressions, geographical industry clustering cannot explain our findings. Moreover, our findings are not driven by the fact that some of the largest cities in the US, like New York, Boston, or Los Angeles are in regions with high CPRATIO. When we include a dummy that is one if the firm is located in one of the ten largest MSAs by population (New York, Los Angeles, Chicago, Miami, Philadelphia, Dallas, Boston, San Francisco, Detroit, and Houston) our results are essentially unchanged. Lastly, we are not capturing effects related to states or state policies as we find, using state fixed effects, that patterns are similar when we analyze within-state variation.

Overall, the CPRATIO results provide strong support for our hypothesis that CEOs subject to the long shot bias tilt capital allocations towards divisions with high skewness. It also lends support to our implicit assumption that decision-making at the headquarter level is responsible for the investment patterns, since we match firms to CPRATIOs by headquarter location. It is important to emphasize that this test allows us to discriminate the CEO long shot bias from other potentially plausible alternative explanations for our findings including, for example, agency problems, career concerns, and risk-taking induced by pay packages. While differences in Catholic and Protestant beliefs and actions when it comes to long shot preferences have been amply documented, it is not obvious why agency, career concerns, or inefficiencies in pay should be more of an issue for otherwise similar firms in Catholic counties than in Protestant counties.

4.2 Additional Evidence

This section provides a range of additional tests to support our conjecture that the CEO long shot bias leads to overinvestment in skewed segments. The first five tests will investigate further if our patterns are related to betting on long-shots, while the remaining three will focus on the role of managerial discretion. Our approach here will be to estimate our benchmark specification (column 4) of Table 2 in subsamples. All results in this section are shown in Table 8, where for conciseness, we report only the two skewness coefficients of interest, namely the skewness variable and its interaction with division size.

First, prior research suggests that betting on long shots becomes more attractive during economic downturns. Evidence for this has been provided in the context of state-lotteries (e.g. Brenner and Brenner (1990) and Mikesell (1994)) and in the context of retail investor behavior, who invest more in lottery type stocks in bad economic conditions (Kumar (2009)). If the investment patterns we document are skewness-related, we would expect to see stronger effects in economic downturns. Using the Chicago Fed National Activity Index to split our sample into periods of economic upswings and downturns, we find exactly this (top panel of Table 8).

Next, we use actual state-level lottery ticket sales data obtained from the North American

Association of State and Provincial Lotteries (NASPL). This data covers 42 states as well as Washington D.C. and Puerto Rico over the period 1990 to 2007. Because this data captures only part of the gambling opportunities for individuals in a state, and because lottery existence and features vary across states, we focus on the year-to-year change in lottery expenditure. Given that data coverage and lottery design does not vary much over time within a state, the change in lottery sales should provide a clean way to identify times of temporarily increased local gambling appetite. We again match firms to states by headquarter location and then split the sample into firms located in states with high and low changes in annual per capita lottery sales. The second panel in Table 8 shows that our skewness-related effects in conglomerate investment are particularly pronounced at times where local gambling propensity is particularly high. This is line with the view that CEOs are influenced by local gambling attitudes and that these gambling attitudes translate into higher investment into skewed segments.

Next, we investigate a potentially important CEO attribute directly. Specifically, we conjecture that younger CEOs would be more aggressive in their investment behavior and more likely to take a long shot. This conjecture is supported by prior work documenting that preference for skewness in investment returns tends to decrease with age (e.g., List (2003), Goetzmann and Kumar (2008), Kumar (2009)). Because we obtain CEO age from the ExecuComp database, we lose more than half of our observations in this test, which affects statistical significance of our estimates. Still, the effect from comparing the oldest CEOs (upper terzile in a given year) to the youngest CEOs is striking. While the point estimates of our coefficients for young CEOs is very similar to our other settings and higher than the benchmark model in Table 2, the effects completely disappear for older CEOs where the point estimates actually indicate that these managers shy away from skewness in their investments. The remarkable differences in the CEO age subsamples underlines our hypothesis that the CEO is pivotal for the investment patterns we observe.

Our next test draws on the well-established fact that the willingness to gamble increases if there is a chance to minimize or even eliminate prior losses (e.g., Kahneman and Tversky (1979), Thaler and Johnson (1990)).[1] We hypothesize that this "gambling for resurrection" effect is also

[1] Thaler and Johnson (1990) show that there exist situations where prior losses exacerbate risk aversion, and where prior gains lead to increased risk seeking (the "house money effect"). However, this behavior is unlikely to be observed in our specific context. First, unlike in the case of a casino gambler who might gamble more fiercely after a surprise win of $1,000 in the first minutes of gambling, it seems hard to think of a CEO as building up winnings (the "house money") that they would then be able to gamble away. Second, as stressed by Thaler and Johnson

relevant in our capital allocation setting. If a firm has recently underperformed the CEO might perceive herself to be in the loss space, which would increase her willingness to bet on a long shot by overinvesting in skewed segments. We do find confirming evidence for this hypothesis when we use the stock return over the last 12 months as a measure of perceived underperformance. We get even stronger results when we use the difference of the current stock price to the 52-week high – an especially salient point of reference for CEOs (e.g., Baker, Pan, and Wurgler (2012)) – as an alternative proxy for firms with CEOs in the loss space. Since the difference to the 52-week high bears no obvious fundamental information, this test is particularly reassuring for our main hypothesis.

Although CEOs have considerable authority in capital allocation decisions, there exist constraints on managerial discretion which make it harder for the CEO to defend a capital allocation that overinvests into skewed segments. Specifically, it will be easier for CEOs to impound their preferences on capital allocations if they are more powerful. We therefore split the sample into firms with high and lower managerial power measured by the Gompers, Ishii, and Metrick (2003) index. As shown in Table 8, we indeed find that our effects are much stronger in corporations which Gompers, Ishii, and Metrick (2003) label "dictatorships".

Another factor that would likely attenuate the tendency of CEOs to overinvest is intensity of competition in the core business of the conglomerate. High competitive pressure induces firms to spent additional resources to obtain more information about how to successfully compete in the industry. This, in turn, will make valuations more precise and would thus limit the scope of allocations the CEO would be able to defend based on "gut feel". We test this using two measures of product market competition used in Giroud and Mueller (2010), the median net profit margin in an industry, and the Herfindahl index of sales within the industry. Consistent with the idea that product market competition puts a constraint on manager's ability to go with their guts, we find that our effects are concentrated in industries where product market competition is weak (high profit margins and high Herfindahl index).

Individually, the tests in this section may not be as sharp as the CPRATIO test because for some of them it is at least conceivable that some other factor is driving the relationship. However,

(1990): *"If prior losses were facilely integrated with subsequent outcomes, we would expect decision makers to be risk seeking for complex losses, just as they are for simple prospects involving losses."* In our setting, prior losses and the capital-allocation-gamble will be integrated *mechanically* via the stock price of the firm. Hence, the prediction will be increased risk-seeking in the loss space.

the CEO long shot hypothesis provides a unifying explanation for these results, while it seems hard to think of an alternative explanation that would collectively explain them. Therefore, in sum, we view these tests as very informative.

5. Alternative Explanations an Discussion

5.1 Agency Problems

In the presence of agency problems, CEOs can strategically exploit valuation uncertainty to tilt capital budgets towards an allocation that maximizes private benefits. The big impact of agency on capital allocation in conglomerates is well established (e.g., Meyer, Milgrom, and Roberts (1992), Scharfstein and Stein (2000), Rajan, Servaes, and Zingales (2000), Stein (2003)).

One common implication of agency models is that resource allocation tends to be "socialistic" – meaning that weak divisions (usually measured by Tobin's Q) are able to get more of the corporate budget than they otherwise would. However, our results are not related to weak divisions in the way agency theory would predict. Tobin's Q for skewed segments is on average *higher* than Tobin's Q for other segments (1.49 vs. 1.29). Moreover, we control for segment fixed effects in Table 3, so the skewness-investment relation cannot be explained by corporate socialism as long as the differences in bargaining power between segments is relatively stable, which appears plausible.

While this already casts doubt on whether the skewness-investment relation can be explained by appealing to agency problems, we provide an additional test. The canonical way to address the principal-agent problem is by granting equity-based compensation (e.g., Jensen and Meckling (1976)). Under the null that the relation is driven by agency problems, using the same logic as a recent paper by Ozbas and Scharfstein (2010), we should therefore observe a weaker skewness-investment relation when managers have more skin in the game via their compensation contracts. Table 9 shows that we find the exact opposite when we split the sample by CEO stock ownership (computed as in Ozbas and Scharfstein (2010)). Effects are strong when managers have high ownership and weak when ownership is low. Hence, skewness affects investment less when agency problems should be more severe. We conclude that a standard agency setting with efficient contracting in which CEOs knowingly distort investment to maximize private benefits, while potentially explaining a substantial fraction of the variation in conglomerate investment in general, does not explain the skewness-investment relation. These findings thus confirm the results based on the CPRATIO test in section 4.1.

It may be useful to point out the relation of the ownership test to the GIM test in Table 8. There we have conjectured that powerful CEOs in "dictatorship" firms would find it easier to go with their guts in making investment decisions. An alternative, agency-based, view would hold that agency problems are more acute in "dictatorship" firms. Hence, the GIM test cannot be used to separate an agency-based explanation from the long shot bias explanation. The ownership test is particularly informative because low ownership is correlated positively with the presence of agency problems. By contrast, it appears implausible to think that CEOs with low ownership are more powerful inside their organization. In fact, there is reason to conjecture the opposite. First, CEOs with higher ownership are more likely to have performed well in the past and to be with the firm for a longer time, both of which would be positively correlated with the standing of a CEO inside the firm. Second, managerial power may actually lead to higher pay (e.g., Bebchuk and Fried (2004)).

The ownership test is therefore valuable in two respects: it shows that the skewness-investment relation is not mainly an agency issue, and – while an in-depth analysis of this point is beyond the aim of this paper – highlights the importance of CEO power in transmitting biases into decisions. It also emphasizes an important difference between agency and managerial biases: since biases operate subconsciously, granting equity-linked pay may have little bite, because CEOs already *think* they are maximizing shareholder value – even though they are not.

5.2 Investment Opportunities

Prior research has documented that CEOs in conglomerates can in some situations also engage in winner-picking that creates value (e.g., Stein (1997), Maksimovic and Phillips (2002)). At first glance, the skewness-investment relation is not related to winner-picking, since Table 6 suggests value destruction in conglomerates with skewed segments, and since CPRATIO is unrelated to investment opportunities. Still, to be conservative, we run some additional tests to rule out that investment in segments with high expected skewness is optimal investment behavior.

First, we include additional controls for investment opportunities in our baseline regressions. We therefore follow Shin and Stulz (1998) and include division sales growth and R&D. Note that we are already controlling for Tobin's Q of division and core segment, and also include industry fixed effects. Panel A in Table 10 shows that our results are not affected, and if anything get stronger when we control for these variables.

As a second test, we look again at investment in stand-alone companies. If the skewness measure is a proxy for good investment opportunities it should predict investment for stand-alone firms just as it does predict investment for conglomerates. The results in Table 10, Panel B show that higher *Skew* also correlates with higher investment for stand-alones when we control only for year effects. Once we control for industry or firm effects, however, skewness does not predict stand-alone investment. So, skewness captures cross-sectional differences across industries, but not time-variation in investment opportunities. By contrast, Tobin's Q – a standard proxy for investment opportunities – at both firm and industry level is a strong predictor of investment once we control for industry or firm effects. In sum, both tests in the section suggest that skewness is not simply proxying for good investment opportunities.

Some comments are in order. First, note that appealing to cash constraints for stand-alones cannot explain why skewness is not related to investment, because even if constraint firms invest less in dollar terms, they would still invest in high skew segments if skewness signals positive NPV projects. Second, the results are consistent with the view that the additional leeway a conglomerate CEO has because of his ability to redistribute capital across divisions is crucial for substantially affecting investment, especially in small segments. This lever is absent for CEOs of single-segment firms.

5.3 Long Shot Bias of Investors

The asset pricing literature suggests that investors like positive skewness in stock returns (e.g., Kumar (2009), Boyer, Mitton, and Vorkink (2010)). Since we focus only on division investment, and not on stock returns, it is not relevant for most results in our paper if investors also like long shots. The results on the value implications in Table 6 are an exception because there we explicitly analyze market valuations of conglomerates with skewed segments.

These regressions present an interesting test of the relative strength of CEO versus market long shot bias. Under the null hypothesis that market participants like long shots more than CEOs, all else equal, we should observe that conglomerates with skewed segments trade at a *premium* because CEOs overinvest in these segments, which is what investors find attractive. Conversely, if the CEO long shot bias dominates, we should observe a discount. While both outcomes are conceivable, the data speak a clear language. They strongly favor the latter alternative, which justifies our focus on the CEO long shot bias in interpreting the results. Effectively, the data is consistent with the view that the many analysts and the thousands of investors who follow General Electric have some ability to judge when the company overestimates the winning prospects of an investment.

The above argument does not take into account the more subtle implications that could arise from combining skewed divisions into a conglomerate. Combining segments might erode skewness. Investors who like skewness may therefore prefer to invest in stand-alones, which could generate a skewness discount for those conglomerates with greater skewness-reduction relative to stand-alones (e.g., Mitton and Vorkink (2011)). While this channel may contribute to explaining the discount, it does not speak to the fact that conglomerates tilt budgets towards skewed segments, and that conglomerates invest more into skewed segments than stand-alones, which are central findings in our paper. To address the issue more formally, we compute the *excess skewness* measure of diversification-induced skewness reduction as in Mitton and Vorkink (2011). In Table A.2 in the appendix we show that adding this variable to our valuation regressions in Table 6 does not alter any of our results. We conclude that the discount for conglomerates with skewed segments that we document is not a result of long shot biased investors who dislike skewness erosion in conglomerates.

5.4 Hard-to-Value Projects and Valuation Mistakes

One implication of valuation uncertainty could also be that CEOs simply make mistakes when allocating capital. We run two tests to show that we are not simply capturing effects related to hard-to-value projects.

First, we try to control for uncertainty directly by including the median idiosyncratic volatility across stand-alone companies in the industry-year in our baseline regressions. Idiosyncratic volatility is measured as the residual from a Fama-French four factor model. Specifications (1) and (2) in Table 11 show that our results on skewness are not related to the variance of returns. As a second test, we follow Green and Hwang (2012) and split the skewness measure in equation (1) into left-skew and right-skew. Right-skew is defined then as $(P_{99} - P_{50})$ and left-skew is defined as $(P_{50} - P_1)$. Columns (3) and (4) in Table 11 present results. As expected, investment is higher when right-skew is higher. Importantly, investment is lower when left-skew is larger. This suggests that it is the long shot property of a division, i.e., the combination of large right-skew and small left-skew, that is driving investment. It is not uncertainty per se because then we would expect to see higher investment also for projects with left-skew since these projects are also harder to value than projects with more symmetric payoff distributions.

6. Conclusion

This paper documents that division investment in conglomerates increases with the expected skewness of the division. The patterns are not explained by established determinants of internal capital allocation or unobservables on the firm or division level. Conglomerates overinvest in segments with high skewness relative to similar stand-alone firms and we find higher discounts for conglomerates with skewed segments relative to other conglomerates and relative to stand-alone firms.

The evidence is most consistent with what we label the "CEO long shot bias". CEOs subject to the long shot bias in conglomerate firms use their decision making authority to channel funds to divisions with higher skewness *because* these segments offer a small change of a large payoff. Potential underlying drivers of the bias include probability weighting in prospect theory, anticipation utility, or the availability heuristic. The long shot bias thus has broad support from decision sciences and is also consistent with survey evidence suggesting that CEOs rely to a considerable degree on "gut feel" when making internal capital allocation decisions. The intuition for our findings is simple: biased CEOs try to pick winners but, because valuation uncertainty is generally high, they end up betting on long shots.

Overall, our results are the first to suggest that the CEO long shot bias is relevant for the allocation of corporate resources in internal capital markets. Our analysis shows that thinking about capital budgeting decisions with an emphasis on (long shot) biased CEOs can yield valuable new insights that add to the more established drivers of capital allocation. Our findings raise important questions for future research: How can we de-bias CEOs? How can we align the actions of biased CEOs with shareholder goals if standard pay contracts are unlikely to be effective because CEOs already think they are maximizing shareholder value? How should we set up effective decision making processes in conglomerates to attenuate the impact of biases? We hope to address some of these issues in further research.

References

Angrist, Joshua, and Joern-Steffen Pischke, 2008, *Mostly Harmless Econometrics* (Princeton University Press).

Baker, Malcolm, Xin Pan, and Jeffrey Wurgler, 2012, A reference point theory of mergers and acquisitions, *Journal of Finance* forthcoming.

Baker, Malcolm, and Jeffrey Wurgler, 2011, Behavioral corporate finance: A survey, *NBER Working Paper Series, No. 17333* August.

Bali, Turan G., Nusret Cakici, and Robert Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Bebchuk, Lucian, and Jesse Fried, 2004, *Pay without performance: the unfulfilled promise of executive compensation* (Harvard University Press).

Benjamin, Daniel J., James J. Choi, and Geoffrey Fisher, 2012, Religious identity and economic behavior, Working Paper, Yale University.

Berger, Philip G., and Eli Ofek, 1995, Diversification's effect on firm value, *Journal of Financial Economics* 37, 39–65.

Berry, Frances S., and William D. Berry, 1990, State lottery adoptions as policy innovations: An event history analysis, *Amerian Political Science Review* 84, 395–415.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Brenner, Reuven, and Gabrielle A. Brenner, 1990, *Gambling and Speculation* (Cambridge University Press, Cambridge, UK).

Brunnermeier, Markus K., and Jonathan A. Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.

Campa, Jose Manuel, and Simi Kedia, 2002, Explaining the diversification discount, *The Journal of Finance* 57, 1731–1762.

Chava, Sudheer, and Amiyatosh K. Purnanandam, 2009, CEOs vs. CFOs: Incentives and corporate policies, *Journal of Financial Economics* forthcoming.

Diaz, Joseph D., 2000, Religion and gambling in sin-city: A statistical analysis of the relationship between religion and gambling patterns in Las Vegas residents, *Social Science Journal* 37, 3.

Ellison, Christopher G., and Kathleen A. Nybroten, 1999, Conservative protestantism and opposition to state-sponsored lotteries: Evidence from the 1997 Texas poll, *Social Science Quarterly* 80, 356–369.

Friedman, Milton, and Leonard J. Savage, 1948, The utility analysis of choices involving risk, *Journal of Political Economy* 56, 279–304.

Giroud, Xavier, and Holger M. Mueller, 2010, Does corporate covernance matter in competitive industries?, *Journal of Financial Economics* 95, 312–331.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Golec, Joseph, and Maurry Tamarkin, 1998, Bettors love skewness, not risk, at the horse track, *Journal of Political Economy* 106, 205–225.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *The Quarterly Journal of Economics* 118, 107–155.

Graham, John R., Campbell R. Harvey, and Manju Puri, 2010, Capital Allocation and Delegation of Decision-Making Authority Within Firms , Working Paper, Duke University.

Green, T. Clifton, and Byoung-Hyoun Hwang, 2012, IPOs as lotteries: Expected skewness and first-day returns, *Management Science* 58, 432–444.

Hirshleifer, David A., Angie Low, and Siew Hong Teoh, 2012, Are overconfident ceos better innovators?, *Journal of Finance* forthcoming.

Hoffman, John P., 2000, Religion and problem gambling in the U.S., *Review of Religious Research* 41, 488–509.

Jensen, Michael C., and William H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305–360.

Kachelmeier, Steven J., and Mohamed Shehata, 1992, Examining risk preferences under high monetary incentives: Experimental evidence from the people's republic of china, *The American Economic Review* 82, pp. 1120–1141.

Kahneman, Daniel, 2011, *Thinking, Fast and Slow* (Macmillan).

——— , and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Kruger, Philipp, Augustin Landier, and David Thesmar, 2011, The wacc fallacy, Working Paper, University of Geneva.

Kumar, Alok, 2009, Who gambles in the stock market?, *Journal of Finance* 64, 1889–1933.

——— , Jeremy Page, and Oliver Spalt, 2011, Religious beliefs, gambling attitudes, and financial market outcomes, *Journal of Financial Economics* 102, 671–708.

Kuppuswamy, Venkat, and Belen Villalonga, 2010, Does diversification create value in the presence of external financing constraints? Evidence from the 2007-2009 financial crisis, Working Paper, Harvard University.

Lamont, Owen, 1997, Cash flow and investment: Evidence from internal capital markets, *The Journal of Finance* 52, pp. 83–109.

List, John A., 2003, Does market experience eliminate market anomalies?, *Quarterly Journal of Economics* 118, 41–71.

Maksimovic, Vojislav, and Gordon Phillips, 2002, Do conglomerate firms allocate resources inefficiently across industries? Theory and evidence, *The Journal of Finance* 57, 721–767.

Malmendier, Ulrike, and Geoffrey Tate, 2005, Ceo overconfidence and corporate investment, *The Journal of Finance* 60, pp. 2661–2700.

Markowitz, Harry, 1952, The utility of wealth, *Journal of Political Economy* 60, 151–158.

Martin, Robert, and Bruce Yandle, 1990, State lotteries as duopoly transfer mechanisms, *Public Choice* 64, 253–264.

Meyer, Margaret, Paul Milgrom, and John Roberts, 1992, Organizational prospects, influence costs, and ownership changes, *Journal of Economics & Management Strategy* 1, 9–35.

Mikesell, John L., 1994, State lottery sales and economic activity, *National Tax Journal* 47, 165–171.

Mitton, Todd, and Keith Vorkink, 2011, Why do firms with diversification discounts have higher expected returns?, *Journal of Financial and Quantitative Analysis* 45, 1367–1390.

Ozbas, Oguzhan, and David S. Scharfstein, 2010, Evidence on the dark side of internal capital markets, *Review of Financial Studies* 23, 581–599.

Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *The Journal of Finance* 55, pp. 35–80.

Scharfstein, David S., and Jeremy C. Stein, 2000, The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *The Journal of Finance* 55, pp. 2537–2564.

Shin, Hyun-Han, and Rene M. Stulz, 1998, Are internal capital markets efficient?, *The Quarterly Journal of Economics* 113, pp. 531–552.

Snowberg, Erik, and Justin Wolfers, 2010, Explaining the favorite-longshot bias: Is it risk-love, or misperceptions?, *Journal of Political Economy* 118, 723–746.

Stein, Jeremy C., 1997, Internal capital markets and the competition for corporate resources, *The Journal of Finance* 52, pp. 111–133.

———, 2003, Agency, information, and corporate investment, *Handbook of Economics and Finance* (edited by George Constantinides, Milton Harris, and Rene Stulz).

Thaler, Richard H., and Eric J. Johnson, 1990, Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice, *Management Science* 36, 643–660.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.

Zhang, Yijie, 2006, Individual skewness and the cross-section of average stock returns, Yale Univeristy, Working Paper.

TABLE 1
Description of the Data Set

This table displays descriptive statistics for the main variables used in our analysis. Panel A reports division-level variables, Panel B reports firm-level variables for the subset of conglomerate firms, and Panel C reports firm-level variables for stand-alone firms. CashFlow is operating profit plus depreciation scaled by total assets. Investment is capital expenditures over lagged assets. R&D is research and development expenses over lagged assets. Size_{DIV} and $\text{Size}_{\text{FIRM}}$ are sales reported in billion dollars. SalesGrowth is sales over lagged sales minus 1. Skew is expected idiosyncratic skewness in division's or firm's FF48-industry. Q_{FIRM} is the bounded Tobin's q defined as $MVA/(0.9 * BVA + 0.1 * MVA)$, where BVA is the book value of assets and MVA is the market value of assets. Q_{DIV} is the median bounded Tobin's q of all stand-alone firms that operate in the same FF48-industry as the division. Q_{CORE} is the median bounded Tobin's q of all stand-alone firms that operate in the same FF48-industry as the largest division of the conglomerate (measured by sales). Beta_{DIV} is the FF48-industry-level asset beta of the division. Age is the current year plus 1 minus the year in which the firm first appeared on Compustat. Focus is sales of the largest division over firm's total sales. Leverage is long-term debt over total assets. See Appendix Table A.1 for a detailed overview of variable definitions.

Panel A: Divisions

Variable	Mean	Median	S.D.	Min.	25^{th} Perc.	75^{th} Perc.	Max.	N
$\text{CashFlow}_{\text{DIV}}$	0.15	0.15	0.21	-0.80	0.07	0.23	0.94	26,818
$\text{Investment}_{\text{DIV}}$ (%)	7.39	4.63	8.92	0.00	1.99	9.09	52.70	26,818
Size_{DIV} ($bn)	0.94	0.14	2.23	0.00	0.03	0.68	14.49	26,818
Skew_{DIV}	0.01	0.01	0.03	-0.07	-0.01	0.03	0.12	26,818
Q_{DIV}	1.39	1.31	0.35	0.97	1.13	1.54	3.09	26,795
Q_{CORE}	1.37	1.31	0.34	0.97	1.12	1.52	2.96	26,789
Beta_{DIV}	0.56	0.54	0.25	0.09	0.40	0.69	1.20	26,818

Panel B: Conglomerate Firms

Variable	Mean	Median	S.D.	Min.	25^{th} Perc.	75^{th} Perc.	Max.	N
Age_{FIRM}	24.86	23.00	14.95	2.00	11.00	38.00	55.00	14,200
$\text{CashFlow}_{\text{FIRM}}$	0.06	0.07	0.12	-0.74	0.04	0.11	0.34	14,200
$\text{Focus}_{\text{FIRM}}$	0.68	0.73	0.24	0.04	0.52	0.89	1.00	14,200
$\text{Investment}_{\text{FIRM}}$ (%)	6.08	4.34	6.42	0.00	2.24	7.65	48.50	14,200
$\text{Size}_{\text{FIRM}}$ ($bn)	2.09	0.39	4.52	0.00	0.07	1.71	26.55	14,200
Q_{FIRM}	1.39	1.20	0.65	0.55	1.01	1.57	5.34	14,197

Panel C: Stand-Alone Firms

Variable	Mean	Median	S.D.	Min.	25^{th} Perc.	75^{th} Perc.	Max.	N
Age_{FIRM}	13.82	10.00	11.38	2.00	6.00	18.00	55.00	65,591
$\text{CashFlow}_{\text{FIRM}}$	0.02	0.06	0.19	-0.74	-0.01	0.12	0.34	65,591
$\text{Investment}_{\text{FIRM}}$ (%)	6.68	3.68	8.92	0.00	1.29	8.14	48.50	65,591
$\text{Size}_{\text{FIRM}}$ ($bn)	0.78	0.08	2.78	0.00	0.02	0.35	26.55	65,591
Q_{FIRM}	1.71	1.35	1.00	0.55	1.03	2.06	5.34	65,563

TABLE 2
Conglomerate Investment and Division Skewness

This table presents results for OLS regressions with division investment as dependent variable. Division investment is defined as division-level capital expenditures in period t scaled by division-level assets in period $t-1$. The division-level skewness (Skew_{DIV}) measures the expected skewness in the division's FF48-industry following Zhang (2006). Size_{DIV} is defined as natural logarithm of division-level sales. All explanatory variables are lagged by one year. See Appendix Table A.1 for detailed variable definitions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

	Dep. Var.: Division investment			
Variable	(1)	(2)	(3)	(4)
Skew_{DIV}	15.789	16.398	17.924	17.811
	(2.99)	(3.17)	(3.53)	(3.54)
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	3.294	3.159	3.112	3.139
	(3.81)	(3.77)	(3.72)	(3.81)
$-\text{Size}_{\text{DIV}}$	0.171	0.132	0.203	0.164
	(1.40)	(1.09)	(1.85)	(1.51)
$\text{CashFlow}_{\text{DIV}}$	3.863	4.179	3.527	3.620
	(5.82)	(6.16)	(5.80)	(5.90)
Q_{DIV}	1.373	1.913	2.161	1.808
	(4.11)	(5.71)	(4.96)	(4.09)
Q_{CORE}	-0.931	0.810	-0.203	0.595
	(-2.86)	(2.25)	(-0.64)	(1.60)
$\text{CashFlow}_{\text{FIRM}}$	8.838	7.715	8.402	8.035
	(7.50)	(6.95)	(7.79)	(7.53)
$\text{Size}_{\text{FIRM}}$	0.017	-0.033	0.064	0.014
	(0.13)	(-0.25)	(0.54)	(0.12)
Age_{FIRM}	-0.484	-0.551	-0.483	-0.518
	(-2.88)	(-3.62)	(-3.16)	(-3.47)
$\text{Focus}_{\text{FIRM}}$	1.013	0.023	0.266	-0.044
	(2.31)	(0.05)	(0.68)	(-0.11)
Year FE	Yes	Yes	Yes	Yes
Industry FE (Firm)	No	Yes	No	Yes
Industry FE (Div)	No	No	Yes	Yes
Observations	26,729	26,729	26,729	26,729
Adjusted R^2	0.040	0.081	0.130	0.138

TABLE 3
Conglomerate Investment, Division Skewness, and Unobservables

This table presents results for OLS regressions with division investment as dependent variable. The baseline regression model (1) from Table 2 is rerun in five different specifications: (1) using first differences of the dependent and independent variables, (2) with firm fixed effects, and (3) with segment fixed effects. In model (4) the dependent variable is defined as division investment less the mean asset weighted investment across all stand-alone companies in the same FF48-industry as in Lamont (1997). In model (5) the dependent variable is the industry-adjusted segment investment (from (4)) less the asset weighted average industry-adjusted segment investment across all the segments of the conglomerate firm (Rajan, Serveas, and Zingales (2000)). The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level in models (1), (4), (5) and at the industry-year level in models (2), (3).

	Changes	Firm FE	Segment FE	Industry Adj.	Industry-Firm Adj.
Variable	(1)	(2)	(3)	(4)	(5)
Skew_{DIV}	10.312	16.772	10.790	25.444	13.042
	(2.38)	(3.19)	(2.40)	(4.72)	(3.09)
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	1.306	3.186	1.949	3.815	1.743
	(1.95)	(4.16)	(2.88)	(4.28)	(2.71)
$-\text{Size}_{\text{DIV}}$	0.053	0.153	1.333	0.148	0.098
	(2.58)	(2.49)	(7.55)	(1.43)	(1.01)
$\text{CashFlow}_{\text{DIV}}$	5.490	4.682	5.967	3.563	2.179
	(6.45)	(10.16)	(8.78)	(5.96)	(3.76)
Q_{DIV}	0.686	1.993	1.270	-1.965	-1.622
	(1.69)	(7.35)	(3.54)	(-5.92)	(-5.01)
Q_{CORE}	0.366	0.165	0.289	-0.267	1.249
	(1.10)	(0.55)	(1.06)	(-0.84)	(4.69)
$\text{CashFlow}_{\text{FIRM}}$	4.626	6.892	5.718	7.930	-2.969
	(4.07)	(7.19)	(5.74)	(6.97)	(-3.72)
$\text{Size}_{\text{FIRM}}$	-3.424	-0.500	0.264	0.048	0.197
	(-9.08)	(-2.73)	(1.28)	(0.42)	(2.02)
Age_{FIRM}	-3.687	-0.932	-1.770	-0.257	-0.080
	(-4.51)	(-2.26)	(-4.47)	(-1.62)	(-0.91)
$\text{Focus}_{\text{FIRM}}$	-0.054	1.091	0.882	0.384	-0.248
	(-0.09)	(2.63)	(2.17)	(0.95)	(-1.03)
Fixed Effect	Year	Firm, Year	Segment, Year	Year	Year
Observations	20,773	26,729	26,729	26,724	26,724
Adjusted R^2	0.032	0.244	0.458	0.028	0.007

TABLE 4
Robustness Checks

This table presents results for OLS regressions with investment as dependent variable for stand-alone firms only. Investment is defined as capital expenditures in period t scaled by assets in period $t-1$. The baseline regression model (1) from Table 2 is rerun in different specifications: (i) using an alternative skewness measure (Skew_{DIV}), which is calculated using 5th (95th) percentile instead of the 1st (99th) percentile of the log return distribution, (ii) using an alternative skewness measure (Skew_{DIV}), which is calculated using daily stock returns from the two preceding fiscal years, (iii) using the MAX measure proposed in Bali, Cakici, and Whitelaw (2011) as alternative skewness measure, it is defined as the average maximum daily log return of all firms in the same FF48-industry over the preceding fiscal year, (iv) includes the average annual return of all firms in the same FF48-industry over the preceding fiscal year, (v) excludes all division operating in a new economy industry (SIC code 3570 to 3579, 3661, 3674, 5045, 5961, or 7370 to 7379), (vi) excludes small divisions with less than \$10 million in sales, (vii) includes the vega of the CEO's option package estimated following Chava and Purnanandam (2009), (viii) includes an overconfident CEO dummy, which equals one if the CEO holds vested options that are at least 67% in the money at the last fiscal year end; average moneyness of the CEOs option portfolio is estimated following Hirshleifer, Low, and Teoh (2012), (ix) includes firm skewness measured as value-weighted average skewness across all divisions of the conglomerate, (x) includes division asset betas estimated using FF48-industry portfolio returns as in Kruger, Landier, and Thesmar (2011), (xi) including only the first half of the sample period, (xii) including only the second half of the sample period. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

	Skew_{DIV}	$t-$ value	$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	$t-$ value	Obs.	Adj. R^2
Alternative Skewness Measures						
Skewness 5%	19.082	3.00	2.786	2.96	26,729	0.040
Skewness 2-years	13.942	1.97	3.589	3.16	26,729	0.040
MAX measure	14.665	4.22	2.007	3.65	26,729	0.041
Other Robustness						
Control for Past Industry Return	13.970	2.65	3.202	3.71	26,729	0.040
Exclude New Economy	16.307	3.05	3.420	3.96	25,800	0.040
Segment Assets > \$10 million	22.521	3.22	4.361	3.92	22,774	0.063
Control for Vega	37.619	2.10	6.043	2.32	7,463	0.072
Control for Overconfidence	38.731	2.05	5.539	2.08	6,601	0.074
Control for Firm Skewness	17.364	3.13	3.273	3.79	26,729	0.040
Control for KLT Beta	16.490	3.13	3.435	3.99	26,729	0.041
1990 - 1999	13.570	2.01	2.811	2.47	18,925	0.031
2000 - 2009	16.832	2.21	3.278	3.02	7,804	0.040

TABLE 5
Conglomerates and Stand-Alone Firms – Matching Results

This table presents results for OLS regressions with the difference in investment between matched pairs, division minus stand-alone firms, as dependent variable. Matching between divisions and stand-alone firms is based on (i) FF48-industry and year, (ii) FF48-industry, year and size using the stand-alone firm closest in size to the division, (iii) FF48-industry, year and size using the stand-alone firm closest in size to the division with a matching threshold of ± 20%, (iv) FF48-industry, year and size using the stand-alone firm closest in size to the division with a matching threshold of ± 20% and age. Age categories are 1-10 and 10+ years. Repeat matches are not allowed. Division and stand-alone firm investment is defined as capital expenditures in period t scaled by assets in period t-1. Skew_{DIV} measures the expected skewness in the FF48-industry following Zhang (2006). Q_{DIV} is defined as median bounded Tobin's q of the FF48-industry. ΔCashFlow is the difference between cash flows over assets of the matched pair, division minus stand-alone firm. All explanatory variables are lagged by one year. See Appendix Table A.1 for detailed variable definitions. The estimation is done for three samples (i) all matched divisions, (ii) only small divisions in the bottom tercile of the size distribution of matched divisions, (iii) only large divisions in the top tercile of the size distribution of matched divisions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the industry-year level.

	Dep. Var.: Δ Investment			
Match by:	Industry, Year	Industry, Year, Size	Industry, Year, Size limit	Industry, Year, Size limit, Age
All Divisions				
Constant	0.141	-0.243	-0.314	-1.076
	(0.35)	(-0.62)	(-0.79)	(-1.73)
Skew_{DIV}	5.813	7.696	8.928	11.100
	(2.30)	(2.97)	(3.27)	(2.46)
Q_{DIV}	-0.361	0.054	0.056	0.818
	(-1.18)	(0.20)	(0.20)	(1.84)
ΔCashFlow	5.837	5.266	6.013	4.635
	(14.82)	(11.17)	(12.30)	(7.51)
Observations	24,205	17,271	16,114	8,736
Adjusted R^2	0.018	0.014	0.017	0.012
Small Divisions (Bottom Relative Size Terzile)				
Skew_{DIV}	15.823	11.275	13.570	17.110
	(3.49)	(2.31)	(2.68)	(2.34)
Controls	Yes	Yes	Yes	Yes
Observations	8,074	5,763	5,377	2,917
R^2	0.011	0.008	0.011	0.010
Large Divisions (Top Relative Size Terzile)				
Skew_{DIV}	1.509	4.475	4.804	4.928
	(0.36)	(1.05)	(1.10)	(0.71)
Controls	Yes	Yes	Yes	Yes
Observations	8,064	5,748	5,365	2,905
Adjusted R^2	0.021	0.022	0.026	0.012

TABLE 6
Value Implications

This table presents results for OLS, fixed effects, instrumental variable, and treatment effects regressions. The sample consists of stand-alone firms and conglomerates. The dependent variable is excess value, which is the log difference between firm value and its imputed value as in Berger and Ofek (1995). Each division of a conglomerate is valued using the median sales multiplier of stand-alone firms in the same FF48-industry that includes at least five firms. The imputed value of the conglomerate is the sum of the division values. Conglomerate is a dummy that is 1 if the firm is a conglomerate and 0 otherwise. In Panel A, Skewed is a dummy variable that is 1 if the conglomerate has a division operating in an industry with above median expected skewness, which is outside the conglomerate's major FF12-industry. In Panel B, #Skewed is the number of skewed segments in the conglomerate. Following Campa and Kedia (2002), the fraction of conglomerate firms in the industry is used as an instrument for conglomerate status in the instrumental variable regressions and the treatment model. The IV regressions also report the p-value of the Angrist and Pischke (2008) F-test for weak instruments. The *t*-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level. All regressions include year dummies and specifications (3) and (4) also include firm fixed effects.

Panel A: At Least One Skewed Segment

	Dep. Var.: Excess Value							
	OLS		FE		IV		Selection	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-0.106	-0.092	-0.099	-0.107	0.104	0.244	0.078	0.199
	(-8.54)	(-6.70)	(-7.70)	(-7.47)	(1.83)	(3.61)	(2.99)	(6.54)
Skewed	-0.042	-0.046	-0.023	-0.018	-0.209	-0.322	-0.198	-0.292
	(-3.26)	(-3.13)	(-2.46)	(-1.79)	(-4.54)	(-5.89)	(-8.39)	(-10.66)
$\text{Size}_{\text{FIRM}}$	0.032	0.223	0.052	0.226	0.027	0.225	0.028	0.224
	(13.84)	(21.18)	(8.62)	(13.69)	(10.11)	(21.15)	(23.75)	(31.47)
CAPX/Sales	0.375	0.227	0.339	0.228	0.384	0.233	0.383	0.232
	(27.91)	(14.83)	(20.97)	(12.31)	(28.23)	(15.13)	(42.44)	(17.17)
EBIT/Sales	-0.050	-0.055	-0.045	-0.069	-0.050	-0.056	-0.050	-0.056
	(-13.78)	(-11.05)	(-9.05)	(-8.75)	(-13.73)	(-11.01)	(-28.31)	(-22.98)
$\text{Size}_{\text{FIRM}}$ (Lag1)		-0.145		-0.220		-0.143		-0.143
		(-14.81)		(-21.81)		(-14.43)		(-15.40)
$\text{Size}_{\text{FIRM}}$ (Lag2)		-0.131		-0.120		-0.138		-0.137
		(-19.57)		(-16.69)		(-20.16)		(-23.64)
CAPX/Sales (Lag1)		0.033		0.040		0.035		0.035
		(3.00)		(2.93)		(3.17)		(2.82)
CAPX/Sales (Lag2)		0.062		0.036		0.070		0.069
		(6.03)		(3.25)		(6.63)		(7.32)
EBIT/Sales (Lag1)		-0.003		-0.001		-0.003		-0.003
		(-1.87)		(-0.28)		(-1.98)		(-2.21)
EBIT/Sales (Lag2)		-0.003		-0.004		-0.003		-0.003
		(-2.56)		(-3.14)		(-2.39)		(-2.85)
Leverage		0.071		0.089		0.059		0.061
		(3.53)		(3.92)		(2.84)		(5.46)

(continued...)

TABLE 6 (Continued)
Value Implications

Panel A: At Least One Skewed Segment (continued)

	Dep. Var.: Excess Value							
	OLS		FE		IV		Selection	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Size}^2_{\text{FIRM}}$		0.009		0.011		0.008		0.008
		(10.81)		(8.23)		(10.00)		(22.22)
Lambda							-0.110	-0.168
							(-7.57)	(-10.02)
Observations	84,973	66,316	84,973	66,316	84,973	66,316	84,973	66,316
Angrist-Pischke F-Test for weak instruments					<0.001	<0.001		

Panel B: Number of Skewed Segments

	Dep. Var.: Excess Value							
	OLS		FE		IV		Selection	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-0.106	-0.091	-0.097	-0.104	0.095	0.232	-0.020	0.048
	(-8.74)	(-6.82)	(-7.57)	(-7.26)	(1.79)	(3.60)	(-1.10)	(2.28)
#Skewed	-0.035	-0.040	-0.027	-0.026	-0.146	-0.231	-0.090	-0.129
	(-3.46)	(-3.53)	(-3.63)	(-3.10)	(-4.65)	(-6.07)	(-6.75)	(-8.41)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	84,973	66,316	84,973	66,316	84,973	66,316	84,973	66,316
Angrist-Pischke F-Test for weak instruments					<0.001	<0.001		

TABLE 7
Geographical Variation in Gambling Propensity and Investment

This table presents subsample results for OLS regressions with division-level investment as dependent variable. We split the sample annually into divisions of conglomerates located in counties with above or below median ratio of Catholics to Protestants our measure of local gambling propensity following Kumar, Page, and Spalt (2011b). Division-level investment is defined as division-level capital expenditures in period t scaled by division-level assets in period $t-1$. The division-level skewness (Skew_{DIV}) measures the expected idiosyncratic skewness in the division's FF48-industry following Zhang (2006). Size_{DIV} is defined as natural logarithm of division-level sales. The large MSA dummy is one for metropolitan statistical areas (MSA) that are among the 10 largest by population in the year 2000. See Appendix Table A.1 for detailed variable definitions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. The table also reports the t-statistic from a Wald-test of equality of coefficients for Skew_{DIV} and $\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$ across regressions (1) and (4), (2) and (5), and (3) and (6), respectively. Standard errors allow for clustering at the firm level.

	Dep. Var.: Division investment					
	Low Gambling Propensity			High Gambling Propensity		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Skew_{DIV}	6.784	6.737	7.736	25.024	24.969	24.866
	(0.87)	(0.86)	(1.00)	(3.59)	(3.59)	(3.63)
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	0.803	0.798	0.988	4.550	4.536	4.635
	(0.59)	(0.59)	(0.74)	(4.28)	(4.26)	(4.43)
$-\text{Size}_{\text{DIV}}$	0.358	0.359	0.293	0.142	0.138	0.149
	(2.89)	(2.89)	(2.33)	(1.14)	(1.11)	(1.19)
$\text{CashFlow}_{\text{DIV}}$	4.881	4.875	4.841	2.613	2.612	2.601
	(5.94)	(5.95)	(5.95)	(3.14)	(3.14)	(3.13)
Q_{DIV}	2.303	2.306	2.263	1.888	1.877	1.852
	(3.27)	(3.27)	(3.23)	(3.55)	(3.53)	(3.51)
Q_{CORE}	0.118	0.118	0.133	-0.188	-0.170	0.071
	(0.23)	(0.23)	(0.26)	(-0.49)	(-0.45)	(0.19)
$\text{CashFlow}_{\text{FIRM}}$	9.493	9.508	9.457	6.956	6.906	6.346
	(5.49)	(5.50)	(5.32)	(5.37)	(5.30)	(4.94)
$\text{Size}_{\text{FIRM}}$	0.214	0.212	0.205	0.038	0.038	0.055
	(1.76)	(1.73)	(1.67)	(0.30)	(0.30)	(0.44)
Age_{FIRM}	-0.607	-0.599	-0.715	-0.341	-0.349	-0.278
	(-2.85)	(-2.75)	(-3.21)	(-1.63)	(-1.66)	(-1.36)
$\text{Focus}_{\text{FIRM}}$	0.507	0.509	0.535	0.219	0.223	0.566
	(0.87)	(0.87)	(0.91)	(0.44)	(0.44)	(1.17)
Large MSA		0.124			-0.180	
		(0.31)			(-0.63)	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (DIV)	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Observations	13,173	13,173	13,173	12,871	12,871	12,871
Adjusted R^2	0.160	0.160	0.167	0.098	0.098	0.110
Wald-test of equality (Skew_{DIV})				1.72	1.72	1.64
Wald-test of equality ($\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$)				2.15	2.15	2.13

TABLE 8
Additional Tests of Skewness Preference

This table presents additional tests for the skewness preference hypothesis. The dependent variable is division-level investment. Division-level investment is defined as division-level capital expenditures in period t scaled by division-level assets in period t-1. The division-level skewness (Skew_{DIV}) measures the expected idiosyncratic skewness in the division's FF48-industry following Zhang (2006). Size_{DIV} is defined as natural logarithm of division-level sales. The control variables are the same as in column 4 of Table 2. The baseline OLS regressions are rerun for different sample splits: (i) negative (positive) Chicago Fed National Activity Index (CFNAI), (ii) high (low) changes in annual per capita lottery sales in the conglomerate's state of location, (iii) old (young) conglomerate firm CEO, (iv) below (above) median stock return (the cumulative return of the conglomerate's stock calculated over the last fiscal year, (v) above (below) median difference between the 52-week high and the stock price at the fiscal year end of the conglomerate firm' stock (scaled by the stock price at the fiscal year end), (vi) above (below) median corporate governance quality of the conglomerate measured by the GIM-Index, (vii) above (below) median product market competition in the conglomerates core business measured by the median net profit margin of the industry, (viii) above (below) median product market competition in the conglomerates core business measured by the Herfindahl index of the industry. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

	Skew_{DIV}	$t-$ value	$\text{Skew}_{\text{DIV}} \times$ $(-\text{Size}_{\text{DIV}})$	$t-$ value	Obs.	Adj. R^2
Chicago FED national activity index						
Negative	22.182	3.13	3.640	3.23	12,085	0.145
Positive	11.867	1.56	2.612	2.16	14,644	0.134
Change in annual per capita lottery sales in the state of location						
High	31.259	2.80	4.936	2.74	6,385	0.114
Low	16.004	1.51	2.565	1.47	6,670	0.118
CEO age						
Young CEOs	32.818	1.36	4.480	1.20	3,240	0.187
Old CEOs	-22.303	-1.14	-2.164	-0.85	3,123	0.242
Share price performance over the last 12 months						
Bad performance	18.444	2.93	3.814	3.76	12,438	0.124
Good performance	15.592	1.81	3.169	2.32	12,314	0.161
52 week high minus current stock price						
Large	26.672	3.04	4.571	3.36	12,467	0.171
Small	8.838	1.24	2.008	1.63	12,644	0.129
GIM index						
Dictatorships	47.843	2.55	7.418	2.79	4,484	0.259
Democracies	5.855	0.37	1.475	0.62	5,994	0.208
Median net profit margin in the conglomerate's major FF48-industry						
High	24.208	3.29	4.271	3.60	12,786	0.155
Low	12.883	1.97	1.842	1.70	13,943	0.122
Herfindahl index of the conglomerate's major FF48-industry						
High	25.112	3.24	4.762	3.83	13,541	0.137
Low	9.962	1.57	1.155	1.07	13,188	0.151

TABLE 9
CEO Ownership and Investment

This table presents subsample results for OLS regressions with division-level investment as dependent variable. We split the sample into divisions with above or below median percentage CEO (of the conglomerate) ownership. Division-level investment is defined as division-level capital expenditures in period t scaled by division-level assets in period $t-1$. The division-level skewness (Skew_{DIV}) measures the expected idiosyncratic skewness in the division's FF48-industry following Zhang (2006). Size_{DIV} is defined as natural logarithm of division-level sales. See Appendix Table A.1 for detailed variable definitions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. The table also reports the t-statistic from a Wald-test of equality of coefficients for Skew_{DIV} and $\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$ across regressions (1) and (4), (2) and (5), and (3) and (6), respectively. Standard errors allow for clustering at the firm level.

	Dep. Var.: Division investment					
	Low CEO Ownership			High CEO Ownership		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Skew_{DIV}	-5.225	-10.312	-8.831	44.199	41.306	44.584
	(-0.25)	(-0.52)	(-0.45)	(2.25)	(2.16)	(2.42)
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	-0.072	-0.705	-0.432	6.663	5.917	6.387
	(-0.03)	(-0.26)	(-0.16)	(2.29)	(2.05)	(2.32)
$-\text{Size}_{\text{DIV}}$	-0.017	0.241	0.016	0.262	0.454	0.275
	(-0.09)	(1.11)	(0.07)	(1.48)	(2.83)	(1.65)
$\text{CashFlow}_{\text{DIV}}$	5.742	4.663	4.399	4.210	4.601	4.053
	(4.65)	(4.18)	(3.87)	(3.31)	(3.59)	(3.25)
Q_{DIV}	2.118	2.973	2.347	0.804	0.191	-0.494
	(3.64)	(3.15)	(2.64)	(1.16)	(0.20)	(-0.50)
Q_{CORE}	1.047	-1.069	0.435	0.872	-0.964	0.781
	(1.78)	(-2.05)	(0.74)	(1.10)	(-1.45)	(0.90)
$\text{CashFlow}_{\text{FIRM}}$	9.468	10.365	10.302	17.428	16.752	17.452
	(3.41)	(4.13)	(3.75)	(4.72)	(4.81)	(4.83)
$\text{Size}_{\text{FIRM}}$	-0.426	-0.114	-0.308	-0.188	-0.132	-0.253
	(-2.19)	(-0.58)	(-1.56)	(-0.85)	(-0.69)	(-1.16)
Age_{FIRM}	0.206	0.278	0.216	-0.594	-0.416	-0.606
	(0.65)	(0.89)	(0.66)	(-1.76)	(-1.22)	(-1.80)
$\text{Focus}_{\text{FIRM}}$	-0.830	0.517	-0.415	0.713	0.127	0.356
	(-0.89)	(0.65)	(-0.51)	(0.89)	(0.15)	(0.45)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE (Firm)	Yes	No	Yes	Yes	No	Yes
Industry FE (Div)	No	Yes	Yes	No	Yes	Yes
Observations	4,889	4,889	4,889	4,994	4,994	4,994
Adjusted R^2	0.054	0.177	0.195	0.062	0.188	0.218
Wald-test of equality (Skew_{DIV})				1.74	1.88	1.98
Wald-test of equality ($\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$)				1.65	1.67	1.76

TABLE 10
Skewness and Investment Opportunities

This table presents results for OLS regressions with division investment as dependent variable in Panel A and investment of stand-alone firms as dependent variable in Panel B. Division and stand-alone firm investment is defined as capital expenditures in period t scaled by assets in period $t-1$. Skew_{DIV} (Skew_{IND}) measures the expected skewness in the division's (stand-alone firm's) FF48-industry following Zhang (2006). Size_{DIV} ($\text{Size}_{\text{FIRM}}$) is defined as natural logarithm of division (firm) sales. All models in Panel A include the same control variables as the baseline regression model (1) from Table 2. All regressions in Panel A and B include year fixed effects. All explanatory variables are lagged by one year. See Appendix Table A.1 for detailed variable definitions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

Panel A: Additional Investment Opportunity Controls

	Dep. Var.: Division Investment			
	(1)	(2)	(3)	(4)
Skew_{DIV}	17.170	18.267	16.991	18.293
	(3.26)	(3.62)	(3.20)	(3.60)
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	3.564	3.273	3.555	3.279
	(4.23)	(4.04)	(4.19)	(4.02)
$\text{SalesGrowth}_{\text{DIV}}$	0.967	0.813		
	(6.92)	(6.28)		
$\text{R\&D}_{\text{DIV}}$			5.305	15.361
			(0.65)	(1.85)
Industry FE (Firm)	No	Yes	No	Yes
Industry FE (Div)	No	Yes	No	Yes
Observations	24,284	24,284	24,284	24,284
Adjusted R^2	0.047	0.149	0.043	0.149

Panel B: Only Stand-Alone Firms

	Dep. Var.: Investment		
	(1)	(2)	(3)
Skew_{IND}	6.592	0.403	1.972
	(4.17)	(0.32)	(0.98)
$\text{Size}_{\text{FIRM}}$	0.126	0.134	-0.634
	(3.34)	(4.48)	(-8.29)
Q_{IND}	-0.659	1.126	0.982
	(-4.21)	(5.90)	(3.46)
$\text{CashFlow}_{\text{FIRM}}$	8.526	6.579	4.383
	(22.76)	(21.89)	(14.00)
Age_{FIRM}	-0.866	-1.066	-1.406
	(-9.26)	(-14.32)	(-9.11)
Q_{FIRM}	1.550	1.637	2.060
	(20.74)	(25.97)	(26.30)
Industry FE	No	Yes	No
Firm FE	No	No	Yes
Observations	65,407	65,407	65,407
Adjusted R^2	0.098	0.308	0.578

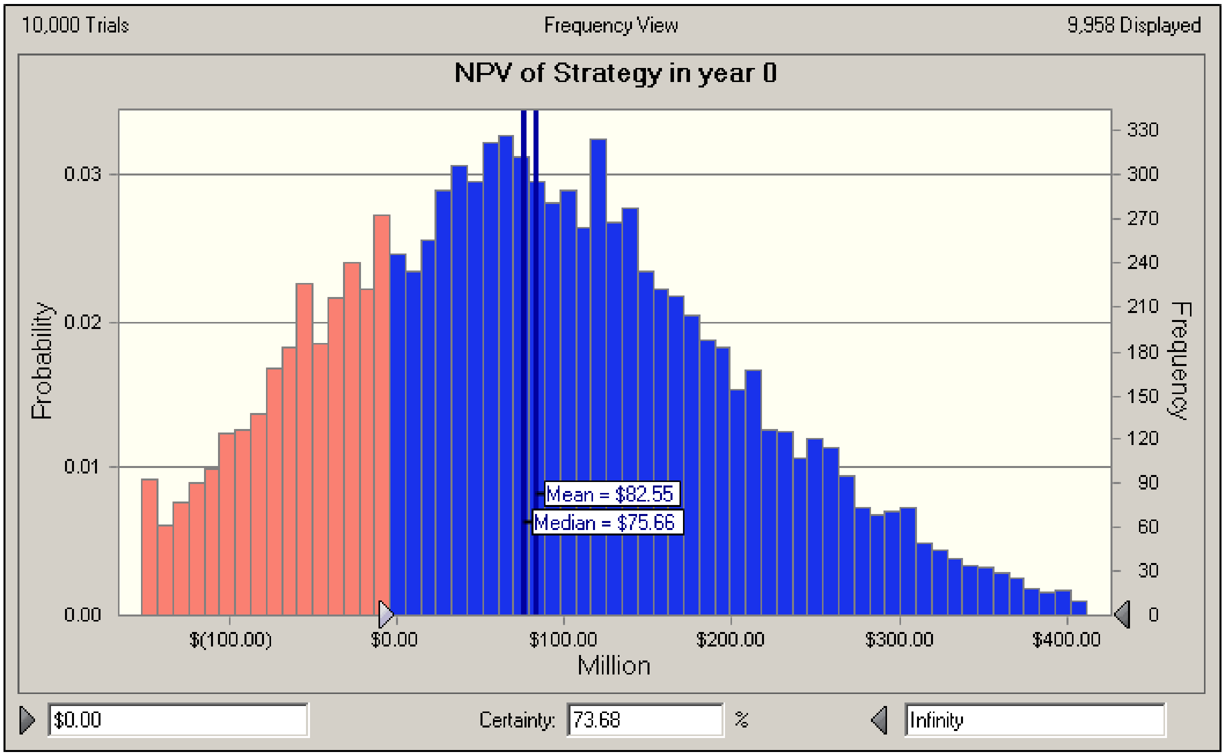
TABLE 11
The Skewness-Investment Relation and Valuation Mistakes

This table presents results for OLS regressions with division investment as dependent variable. Division investment is defined as division-level capital expenditures in period t scaled by division-level assets in period $t-1$. The division-level skewness (Skew_{DIV}) measures the expected skewness in the division's FF48-industry following Zhang (2006). Size_{DIV} is defined as natural logarithm of division-level sales. Volatility is the median idiosyncratic volatility in the division's FF48-industry. $\text{RightSkew}_{\text{DIV}}$ ($\text{LeftSkew}_{\text{DIV}}$) is defined as the difference between the 99th and 50th (50th and 1st) percentile of the daily return distribution of stocks in the division's FF48-industry over the preceding fiscal year. All regressions include the same control variables as the baseline regression model (1) from Table 2. All explanatory variables are lagged by one year. See Appendix Table A.1 for detailed variable definitions. The t-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

	Dep. Var.: Division Investment			
	(1)	(2)	(3)	(4)
Skew_{DIV}	15.330	17.453		
	(2.92)	(3.49)		
$\text{Skew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	3.172	3.060		
	(3.69)	(3.74)		
$\text{Volatility}_{\text{DIV}}$	41.626	24.861		
	(2.00)	(1.05)		
$\text{Volatility}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$	9.563	7.700		
	(2.90)	(2.30)		
$\text{RightSkew}_{\text{DIV}}$			57.055	53.620
			(3.10)	(3.00)
$\text{RightSkew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$			10.836	9.743
			(3.52)	(3.25)
$\text{LeftSkew}_{\text{DIV}}$			-48.461	-55.930
			(-2.73)	(-3.23)
$\text{LeftSkew}_{\text{DIV}} \times (-\text{Size}_{\text{DIV}})$			-9.724	-9.693
			(-3.26)	(-3.36)
Year FE	Yes	Yes	Yes	Yes
Industry FE (Firm)	No	Yes	No	Yes
Industry FE (Div)	No	Yes	No	Yes
Observations	26,729	26,729	26,729	26,729
Adjusted R^2	0.040	0.139	0.040	0.138

FIGURE 1
Valuation Uncertainty – Simulating NPV for an Investment Project

This figure shows results from a simulation of NPV for a typical investment project. Inputs include distributional assumptions on sales growth, margins, ability to expand production in the future if the project goes well, as well as on several cost overrun factors. Additional inputs are the correlations between these random variables. The model is sophisticated, and may use all available information available to the decision maker. As shown in the distribution of NPVs, the resulting standard error around the mean estimate is still substantial. "Valuation uncertainty" is large.



Appendix

TABLE A.1

Variable Definitions and Sources

This table briefly defines the main variables used in the empirical analysis. The data sources are: (i) ARDA: Association of Religion Data Archives, (ii) Compustat, (iii) CRSP: Center for Research on Security Prices. Table I reports the summary statistics for all these variables, (iv) NASPL: North American Association of State and Provincial Lotteries.

Variable name	Description	Source
Division-level variables		
$Investment_{DIV}$	Division-level capital expenditures [CAPX] scaled by division-level assets [AT] at the previous fiscal year end.	Compustat
$Skew_{DIV}$	Expected idiosyncratic skewness is estimated following Zhang (2006): $$SKEW_{i,t} = \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{(P_{99} - P_1)} \quad (3)$$ where P_j is the jth percentile of the log return distribution pooled across all firms within the same FF48-industry of division i over its preceding fiscal year.	CRSP
$SalesGrowth_{DIV}$	Sales [SALE] over lagged sales minus one.	Compustat
$R\&D_{DIV}$	R&D expenses [RD] scaled by lagged assets [AT]. Missing R&D expenses are set to zero.	Compustat
$Size_{DIV}$	Natural logarithm of division-level sales [SALE].	Compustat
$CashFlow_{DIV}$	Division-level cash flows [OPS+DP] scaled by division-level assets [AT].	Compustat
ΔCashFlow	Difference between $CashFlow_{DIV}$ and $CashFlow_{FIRM}$ of the matched stand-alone firm	Compustat
ΔInvestment	Difference between $Investment_{DIV}$ and $Investment_{FIRM}$ of the matched stand-alone firm.	Compustat
Q_{DIV}	Median bounded Tobin's Q of all stand-alone firms that operate in the same FF48-industry as the division. The bounded Tobin's Q is defined following Ozbas and Scharfstein (2010) as $MVA/(0.9 * BVA + 0.1 * MVA)$, for further details see Q_{FIRM}.	Compustat
$Beta_{DIV}$	Industry-level asset beta are estimated following Kruger, Landier, and Thesmar (2011) in two steps: (i) industry-level equity betas are estimated by regressing monthly returns of the FF48-industry portfolios on the CRSP value weighted market index for moving windows of 60 months, (ii) industry-level equity betas are unlevered using the average market leverage observed in each FF48-industry.	CRSP, Compustat

(continued...)

TABLE A.1 (Continued)

Variable Definitions and Sources

Variable name	Description	Source
Firm-level variables		
$Investment_{FIRM}$	Firm's total capital expenditures [CAPX] scaled by firm's total assets [AT] at the previous fiscal year end.	Compustat
$CashFlow_{FIRM}$	Firm' total cash flows [IB+DP] scaled by firm's total assets [AT].	Compustat
$SalesGrowth_{FIRM}$	Sales [SALE] over lagged sales minus one.	Compustat
$R\&D_{FIRM}$	R&D expenses [XRD] scaled by lagged assets [AT]. Missing R&D expenses are set to zero.	Compustat
$Size_{FIRM}$	Natural logarithm of firm's sales [SALE].	Compustat
Age_{FIRM}	Natural logarithm of the current year plus one minus the year in which the firm first appeared in the Compustat North America database.	Compustat
$Focus_{FIRM}$	Ratio of the core (largest) division sales and the firm's total sales [SALE]. Equals one for stand-alone firms by definition.	Compustat
Q_{FIRM}	The bounded Tobin's Q is defined following Ozbas and Scharfstein (2010) as $MVA/(0.9 * BVA + 0.1 * MVA)$, where BVA is the book value of assets [AT] and MVA is the market value of common equity [CSHO*PRCC_F] plus the book value of assets [AT] minus the book value of common equity [CEQ] and balance sheet deferred taxes [TXDITC].	Compustat
Leverage	Long-term debt [DLTT] over total assets [AT]	Compustat
Large MSA	Largest ten MSAs by population as of the year 2000.	US Census
Other variables used		
CPRATIO	Ratio of Catholic population to Protestant population in the county where the conglomerate firm's headquarter is located.	ARDA, US Census
CFNAI	The CFNAI is a weighted average of 85 existing monthly indicators of US economic activity. It is constructed to have an average value of zero and a standard deviation of one. A positive index corresponds to growth above trend and a negative index corresponds to growth below trend.	Chicago Fed
CEO Age	Age of the conglomerate firm's CEO at the fiscal year end.	ExecuComp
CEO Overconfidence	1 if the CEO holds vested options that are at least 67% in the money at the last fiscal year end; average moneyness of the CEOs option portfolio is estimated following Hirshleifer, Low, and Teoh (2012).	ExecuComp
CEO Ownership	Percentage stock ownership of the conglomerate firm's CEO.	ExecuComp
CEO Vega	Vega of the CEO's option package estimated following Chava and Purnanandam (2009).	ExecuComp
GIM-Index	Following Gompers, Ishii, and Metrick (2003), minimum 1 (low entrenchment), maximum 19 (high entrenchment).	A. Metrick's website
Product Market Competition (Herfindahl)	Herfindahl index (sum of squared market shares measured in sales) in the core division's FF48-industry.	Compustat
Product Market Competition (NPM)	Median net profit margin [OIBDP/SALE] in the core division's FF48-industry.	Compustat
Return Past 12 Months	Cumulative return of the conglomerate firm's stock calculated over the last fiscal year.	CRSP
Difference to 52 Week High	Difference between the 52-week high and the stock price at the fiscal year end of the conglomerate firm' stock, scaled by the stock price at the fiscal year end. The 52-week high is defined as the highest share price during the last fiscal year.	CRSP
ΔLotteryTicketSales	Annual change in per capita lottery expenditures in the state where the conglomerate firm's headquarter is located.	NASPL

TABLE A.2
Value Implications (Controlling for Excess Skewness)

This table shows results from adding a control for excess skewness to the specifications in Table 6. Excess skewness is defined following Mitton and Vorkink (2010). It is the difference between the return skewness of a firm and its imputed skewness. Return skewness is the third standardized moment of 12 monthly returns. Imputed skewness is the weighted average of the skewness measures from each segment. For each segment in a given FF48 industry, skewness is taken to be the the median return skewness of all stand-alone firms in the FF48-industry. We require at least 5 firms in the industry and year to calculate skewness. Following Campa and Kedia (2002), the fraction of conglomerate firms in the industry is used as an instrument for conglomerate status in the instrumental variable regressions and the treatment model. The IV regressions also report the p-value of the Angrist and Pischke (2008) F-test for weak instruments. The base and additional control variables are same as in the respective regressions in Table 6. The *t*-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level. All regressions include year dummies and specifications (3) and (4) also include firm fixed effects.

Panel A: At Least One Skewed Segment

	Dep. Var.: Excess Value							
	OLS		FE		IV		Selection	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-0.115	-0.112	-0.099	-0.124	0.048	0.036	0.255	0.206
	(-8.14)	(-6.96)	(-6.47)	(-7.03)	(0.78)	(1.09)	(3.59)	(5.61)
Skewed	-0.053	-0.032	-0.049	-0.018	-0.177	-0.179	-0.325	-0.304
	(-3.45)	(-2.58)	(-2.87)	(-1.37)	(-3.58)	(-6.15)	(-5.71)	(-9.25)
Excess Skewness	-0.056	-0.056	-0.049	-0.048	-0.057	-0.057	-0.049	-0.049
	(-13.70)	(-15.60)	(-10.97)	(-12.65)	(-13.76)	(-14.56)	(-10.66)	(-11.25)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	46,317	46,317	37,259	37,259	46,317	46,317	37,259	37,259
Angrist-Pischke F-Test for weak instruments					<0.001	<0.001		

Panel B: Number of Skewed Segments

	Dep. Var.: Excess Value							
	OLS		FE		IV		Selection	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-0.116	-0.111	-0.100	-0.122	0.039	-0.045	0.236	0.046
	(-8.42)	(-6.97)	(-6.69)	(-6.97)	(0.66)	(-1.94)	(3.51)	(1.78)
#Skewed	-0.044	-0.032	-0.041	-0.022	-0.124	-0.088	-0.223	-0.130
	(-3.69)	(-3.18)	(-3.13)	(-2.02)	(-3.70)	(-5.34)	(-5.74)	(-7.14)
Excess Skewness	-0.056	-0.056	-0.049	-0.048	-0.057	-0.056	-0.049	-0.049
	(-13.69)	(-15.59)	(-10.97)	(-12.65)	(-13.74)	(-14.55)	(-10.65)	(-11.42)
Base controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	46,317	46,317	37,259	37,259	46,317	46,317	37,259	37,259
Angrist-Pischke F-Test for weak instruments					<0.001	<0.001		