Firm Complexity and Limits to Arbitrage

Alexander Barinov

School of Business
University of California Riverside

E-mail: **abarinov@ucr.edu**
http://faculty.ucr.edu/~abarinov

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Abstract

Several important anomalies are stronger for more complex firms. Despite conglomerates being on average larger and more liquid than single-segment firms, anomalies are stronger for conglomerates. In the conglomerates-only subsample, anomalies are stronger for conglomerates with more between-segments difference in market-to-book and operating leverage.

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1 Introduction

Several recent papers show that organizational complexity of conglomerates affects future returns due to complexity adversely affecting investors' ability to process value-relevant information. Cohen and Lou (2012) show that conglomerates, defined as firms that have business segments with different two-digit SIC codes, take two to four weeks longer to incorporate industry-level news: returns to a pseudo-conglomerate, calculated as weighted average of average returns of single-segment firms in the same industry as the segments of the real conglomerate, predict returns to the real conglomerate two to four weeks ahead. Barinov et al. (2019) find similar evidence looking at post-earnings-announcement drift (PEAD): conglomerates have more delayed response to their own earnings news than single-segment firms. Barinov (2018) shows that conglomerates have higher analyst disagreement and larger earnings forecast errors than peer firms and thus, following the logic of Miller (1977), are overpriced in the presence of short-sale constraints: short-sale constraints keep (some) pessimistic investors out of the market, and the stock price is then the average valuation of the remaining optimists, which naturally increases as optimists disagree more and hold more extreme (positive) opinions about the stock.

This paper suggests using firm complexity as a limits to arbitrage variable. Conglomerates and especially more complex conglomerates, with more numerous and more diverse segments, are hard to analyze and investors need to spend considerable resources to arrive at their fair value. Thus, anomalies will be stronger for conglomerates, as investors would be more willing to deal with single-segment firms and trade against anomalies in the sample that includes such firms. Only as such trading opportunities are exhausted will investors trade against anomalies in the conglomerate subsample.

There are multiple reasons why conglomerates are harder to value than single-segment firms. First, the person doing the valuation has to have expertise in several industries the conglomerate operates in, as compared to just one industry for a comparable single-segment firm. Second, conglomerates tend to transfer funds between their divisions, which can confuse the outside investor. In particular, the outside investor can find difficult ascribing the overhead to each division in a way that accurately represents the true operating leverage of the divisions. Third, conglomeration has benefits (synergies between the lines of business and potential coinsurance in the form of supporting a temporarily suffering division using funds from the other division(s)) as well as costs (loss of management efficiency, inefficient distribution of resources between divisions motivated by "fairness" or inter-firm politics). To arrive at the fair value of a conglomerate, one has to weigh these costs and benefits and form an expectation as to their future relative importance.

The paper uses several measures of conglomerate complexity. The simplest complexity measure, NSeg, is the number of business segments with different two-digit SIC codes. As a conglomerate spreads out across more industries, more diverse expertise is needed to understand the state of every segment. Costs and benefits of conglomeration also become more complicated as the number of segments increases.

The second complexity measure, *1-HHI*, looks at sales concentration in the conglomerate's segments. The logic of the *1-HHI* measure is that a two-segment conglomerate with 95% of sales concentrated in one segment is very close to a single-segment firm (its *1-HHI* measure equals 0.095, and any single-segment firm has *1-HHI* measure equal to 0 by definition), while a two-segment conglomerate with 50-50 split of sales between two industries is significantly more complex (its *1-HHI* measure equals 0.5).

Three more complexity measures look at how different segments of a conglomerate are. The RSZ measure is the coefficients of variation (the ratio of standard deviation to average) of segments' imputed market-to-book (defined as the average market-to-book of single-segment firms with the same two-digit SIC code as the segment, as the market value of the segment, needed to compute its own market-to-book, in unavailable). The RSZ measure is motivated by Rajan et al. (2000), who relate a similar segment diversity measure based on Tobin's q to the magnitude of diversification discount and argue that more diverse segments can generate more misallocation of resources, for example, due to the desire of the headquarters to keep divisions "more equal", which would result in an inefficient transfer of funds from high-q, fast-growing segments to low-q, low-growth segments. The extent of this inefficient transfer and its impact on firm value is hard to estimate; it is also hard to find an analyst with enough expertise in two or more very different industries. Both of those reasons make conglomerates with higher RSZ measure more complex.

The other two measures of segment diversity, CV_{OL} and CV_{SGA}, are coefficients of variation of imputed operating leverage. For CV_{OL}, operating leverage is costs of goods sold (COGS) plus sales, general, and administrative expenses (SG&A) divided by total assets. For CV_{SGA}, operating leverage is just SG&A over total assets. Both measures use imputed values of operating leverage, since allocating the overhead across divisions and estimating properly the operating leverage of each division is a major challenge in conglomerate valuation. The greater is the difference in operating leverage between segment, the greater are the potential errors of mis-estimating segment-level operating leverage and the higher is the conglomerate's complexity.

The empirical tests in paper start with showing that, compared to peer single-segment firms, conglomerates tend to have lower number of analysts following the firm, lower earnings quality, larger earnings forecast errors and lower institutional ownership. Among conglomerates, these negative effects of firm complexity are more pronounced among more complex conglomerates, e.g., ones with more diverse business segments.

The relatively poor information environment of conglomerates and the relative absence of smart money in the market for their shares will exacerbate mispricing: similar to institutions, other investors can be deterred from trading against anomalies in the conglomerate subsample due to conglomerates having lower earnings quality and worse analyst coverage, as well as other challenges of valuing a conglomerate outlined above. Indeed, I find, both in portfolio sorts and cross-sectional regressions, that several important anomalies, such as the idiosyncratic volatility effect of Ang et al. (2006), the asset growth effect of Cooper et al. (2008), and turnover effect of Datar et al. (1998), are stronger for conglomerates despite conglomerates being, on average, more than twice larger and significantly more liquid than single-segment firms.

Within the conglomerate sample, anomalies are stronger for conglomerates with higher business complexity: i.e., for conglomerates with a greater number of business segments, or with sales being more dispersed across segments, or with segments more diverse in terms of their growth opportunities or their operating leverage. Again, the conclusion that anomalies are stronger for more complex conglomerates holds both in portfolio sorts and cross-sectional regressions.

Firm complexity is distinct from other arbitrage variables suggested in the literature, such as idiosyncratic volatility, institutional ownership, size, firm age, etc. The traditional limits to arbitrage variables are strongly related to size, and their use in asset-pricing tests repeatedly affirms that anomalies are stronger for small illiquid firms. It is not clear therefore whether many established relations between anomalies and limits to arbitrage can be used as a guidance by investors who trade against the anomalies or as evidence that the anomalies violate market efficiency. For example, if an anomaly is strong for highly volatile firms that are usually small and illiquid, the cost of trading against it in this subsample can be extreme and take away a large fraction of before-cost alphas reported by conventional asset-pricing tests.

Conglomerates, on the other hand, tend to be large liquid firms. The evidence presented in this paper that several anomalies are stronger for conglomerates runs counter to all other potential relations of anomalies with limits to arbitrage variables. This evidence also more clearly violates market efficiency and can serve as a basis of a profitable trading strategy, since trading against an anomaly in the conglomerate subsample is unlikely to be very costly.

2 Data Sources and Main Variables

The paper considers eight anomalies: the idiosyncratic volatility effect of Ang et al. (2006), the analyst disagreement effect of Diether et al. (2002), the turnover effect of Datar et al. (1998), the turnover variability effect of Chordia et al. (2001), the investment growth effect of Anderson and Garcia-Feijoo (2006), the asset growth effect of Cooper et al. (2008), the cumulative issuance puzzle of Daniel and Titman (2006), and the retained earnings effect of Ball et al. (2020).

Following Ang et al. (2006), idiosyncratic volatility (IVol) is defined as standard deviation of residuals from the three-factor Fama and French (1993) model fitted to daily returns in each firm-month. Factor returns are from Kenneth French's website[1], stock returns come from CRSP daily return file. Analyst disagreement (Disp) is standard deviation of analyst earnings forecasts for the current fiscal year earnings divided by the consensus forecast (both are from IBES consensus estimates file). Turnover (Turn) is the annual average of the ratio of trading volume to shares outstanding (both from CRSP monthly return file). Turnover variability (CVT) is standard deviation of turnover divided by average turnover, with both the standard deviation and the average computed over the

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

past 36 months and updated monthly. Asset growth (AG) and investment growth (IG) are annual growth rates of total assets and capital expenditures, respectively. Cumulative issuance (CI) is the difference between the log market cap growth of the firm and the log cumulative returns of the same firm in the past five years. Retained earnings over market (RE) is the ratio of retained earnings to market cap at the end of the fiscal year.

The paper also uses six alternative measures of complexity. *Cong*, the conglomerate dummy, equals one if the firm reports more than one segment with different two-digit SIC codes on the Compustat segment file, and zero if the firm is on the Compustat segment file, but either reports one business segment or has all its segments within the same two-digit SIC code. *NSeg* is the number of segments with different two-digit SIC codes (conglomerates with more segments in different industries are assumed to be more complex). *1-HHI* measures the concentration of sales in the conglomerate segments using Herfindahl index (HHI) and then deducts this index from 1. The segment sales are from the Compustat segments file. By definition, single-segment firms have *1-HHI*=0.

Three more measures attempt to measure the differences between the industries the conglomerate operates in by looking at diversity of market-to-book (*RSZ* measure) and operating leverage (CV_{OL} and CV_{SGA} measures). Since segment-level data to compute market-to-book and operating leverage are not available, the measures use imputed values, i.e., each segment is assumed to have the average market-to-book or operating leverage of single-segment firms (from the Compustat segment file) with the same two-digit SIC code. All measures of segment diversity are coefficients of variation (the ratio of standard deviation to average) of either segments' imputed market-to-book (RSZ) or segments' imputed operating leverage (CV_{OL} and CV_{SGA}) within the conglomerate. Both the standard deviation and the average use segment sales (from the Compustat segment file) as weights. CV_{OL} defines operating leverage as the sum of cost of goods sold (COGS) and sales, general, and administrative expenses (SG&A) divided by total assets, while CV_{SGA} looks only at SG&A-to-assets ratio. By definition, single-segment firms have the segment diversity measures equal to zero.

All tests in the paper use the maximum available sample: for example, if a regression uses institutional ownership, the sample includes only firms with non-missing institutional ownership, but if the next test requires only IVol and RSZ to be non-missing, then firms with missing institutional ownership will be included in this test.

The sample in the paper is from January 1978 to December 2018 (based on availability of Compustat segments data). Detailed definitions of other variables used in the paper are in the Data Appendix.

3 Firm Complexity and Other Firm Characteristics

3.1 Firm Complexity, Size, and Liquidity

Panel A of Table 1 looks at market cap and several liquidity measures for groups of firms with different complexity. The liquidity measures are three measures of effective bid-ask spread (the Roll (1984) measure, the effective tick of Holden (2009), the Corwin and Schultz (2012) measure), the Amihud (2002) price impact measure, and the fraction of zero-return days suggested by Lesmond et al. (1999), who argue that investors trade when benefits of trading exceed trading costs, and thus the frequency of situations when investors do not trade, perceiving trading costs to be greater than benefits of trading, proxies for trading costs. Panel A also looks at the level of stock price, which is known to be related to liquidity.

The first four columns of Panel A tabulate medians of those measures for single-segment firms and conglomerates and then look at the differences between those two types of firms (the fourth column reports the t-statistics for the differences). Panel A shows that a representative conglomerate is roughly 2.5 larger than a representative single-segment firm, its stock has a price that is 80% higher, sees 33% less no-trade days, has effective bid-ask spread 40-80% lower (depending on the measure used), and price impact four times smaller than that of single-segment firms. All differences are statistically significant, which confirms that conglomerates are larger, more liquid, and thus less likely to be mispriced all else equal.

The next two columns partition conglomerates into low- and high-complexity ones based on whether their CV_{OL} measure of segment diversity is above the median. Panel A reveals that high-complexity conglomerates are 7% smaller than low-complexity conglomerates, but also slightly more liquid than low-complexity ones. The differences are statistically significant, but mostly economically small: price level is 4% larger and effective bid-ask spread 2-5.5% smaller for high-complexity conglomerates, while the Amihud price impact measure is 25% lower for high-complexity conglomerates. The last two columns of Panel A also look at the difference in size and liquidity between single-segment firms and low-complexity conglomerates and find that this difference is very close to the difference between single-segment firms and all conglomerates in columns three and four.

In untabulated results, I split conglomerates into low- and high-complexity ones using other measures of complexity and find that the results are similar: with the exception of the split on number of segments, high-complexity conglomerates are slightly larger and more liquid than low-complexity ones. Splitting conglomerates on number of segments (two segments vs. three segments or more, the median number of segments is two in almost all years) produces wider spread in size and liquidity: conglomerates with three-plus segments are almost twice larger than two-segment conglomerates, have 70% smaller price impact, 50% larger stock price, 23% less no-trade days, and 18-34% smaller effective bid-ask spread.

The conclusion from Panel A of Table 1 is that firm complexity and especially conglomerate status are positively related to size and negatively related to trading costs, which makes complexity a special limits-to-arbitrage variable that is unlikely to pick up the effects of other limits-to-arbitrage variables that usually label small illiquid firms as firms with high limits to arbitrage.

3.2 Firm Complexity and Information Environment

Panel B of Table 1 uses firm complexity as one of determinants of the firm information environment by introducing CV_{OL} complexity variable in multiple regressions of number of analysts covering the firm, institutional ownership of the firm's shares, analyst forecast errors and earnings quality on their known determinants. I follow Peterson (2009) and perform panel regressions with errors clustered by firm-month or firm-quarter, based on the frequency of the dependent variable.

The drivers of analyst coverage in the first column of Panel B are from Hong, Lim, and Stein (2000) and include firm size, market-to-book, return volatility, and returns in the past two years. I add to this list firm age, profitability, and dummy for operating loss. The first column of Panel B reveals that controlling for this long list of variables, firms with more diverse business segments have significantly smaller number of analysts covering them. The second column confirms this result focusing on a particular type of analysts that specialize in the industry the firm is in (for conglomerates, that would be the industry of the largest segment). Hence, conglomerates not only have less analyst coverage than comparable single-segment firms, but the coverage is also of worse quality, since analysts covering conglomerates are more likely to lack expertise in the conglomerate's main business.

The conclusion of worse quality of analyst coverage is supported by column five, which uses absolute values of earnings forecast errors made by analysts (the forecast errors are scaled by consensus EPS forecast). Column five uses controls from Thomas (2002) and adds number of analysts following the firm and the operating loss dummy as additional controls. Reliably positive slope on the segment diversity measure indicates that analysts make larger errors forecasting earnings of conglomerates.

The third column in Panel B uses institutional ownership as the dependent variable and shows that the troubles analysts have when covering conglomerates are shared by institutions that hold conglomerates' stocks. Institutions, similar to analysts, tend to abandon conglomerates in favor of single-segment firms with similar characteristics: controlling for the traditional determinants of institutional ownership from Gompers and Metrick (2001) and the operating loss dummy, I observe that institutional ownership is significantly and negatively related to my measure of conglomerate diversity.

Another potential reason why institutional investors tend to avoid conglomerates (in addition to conglomerates having worse analyst coverage and higher analyst forecast errors) is given in column four of Panel B that looks at earnings quality. I measure earnings quality as coefficient of variation (standard deviation over average) of discretionary accruals from the modified Jones (1991) model (see Dechow et al., 1995) - lower variability of discretionary accruals is assumed to be synonymous to higher earnings quality. The determinants of earnings quality are collected from a review paper by Dechow et al. (2010) and include firm size, stock returns volatility, firm age, leverage, investment, sales growth, profitability and the operating loss dummy. Controlling for these variables that pick up both incentives to manage earnings and potential costs of doing so, as well as firm environment characteristics that make earnings a less reliable signal of firm performance, I find in column four of Panel B that more complex firms have lower earnings quality. Beyond making professional investors avoid conglomerates, lower earnings quality can be a reason why analysts choose not to follow conglomerates if otherwise similar single-segment firms are available.

The results in Panel B of Table 1 are robust to using alternative measures of complexity like the RSZ measure (segment diversity in terms of imputed market-to-book) or *1-HHI* measure that looks at concentration of sales in the segments or a simple count of number of segments. However, all complexity measures have a large mass at zero (or one for the number of segments), which stands for low/zero level of organizational complexity of single-segment firms. Hence, the question arises of whether the results in Panel B are just about conglomerates vs. single-segment firms or whether higher-complexity conglomerates also have worse analyst coverage, smaller institutional ownership, and lower earnings quality. To this end, in Panel C I repeat the regressions in Panel B restricting the sample to conglomerates only.

I find that the main result of Panel B - the negative relation between complexity and information environment - is quite robust to looking only at conglomerates. The significant negative relation between firm complexity on the one hand and analyst coverage and institutional ownership on the other is preserved in Panel C. The positive relation between complexity and analyst forecast errors becomes insignificant, and the same is true about the negative relation between complexity and earnings quality, though the latter relation does not become numerically smaller, and its insignificance can be attributed to the fact that the sample decreases roughly by a factor of three (about 70% of firms in my sample are single-segment firms, and only 30% are conglomerates).

Restricting the sample to conglomerates in Panel C of Table 1 also makes easier the interpretation of the economic magnitude of the slopes on firm complexity. The complexity variable, as well as all dependent variables except for institutional ownership, are in logs. In the conglomerates-only subsample, the complexity variable roughly quadruples between its 25th and 75th percentile and increases by a factor of 18 from the 10th to 90th percentile. The latter change will cause the number of analysts following the conglomerate to drop by almost 50% (equals to loss of four analysts for a conglomerate with the average analyst following of eight analysts) and the number of specialist analysts to drop by about 60% (a similar loss of 2.6 out of 4.3 specialists following an average conglomerate). The institutional ownership for otherwise similar conglomerates at the 10th and 90th percentile of complexity will change by 25% (a large effect compared to 54% institutional ownership for an average conglomerate), and the insignificant point estimates for earnings quality and analyst forecast error imply that the former will deteriorate by 33% and the latter by 14% if firm complexity shifts from the 10th to 90th percentile.

The caveat about the effect of complexity in Panels B and C is that it is measured holding everything else, including the size of the company, fixed. In unconditional tests (untabulated) conglomerates have marginally (by roughly 10%) higher number of specialists following them, higher earnings quality, and higher institutional ownership than single-segment firms due to conglomerates being twice larger (see Panel A of Table 1). The unconditional spread between conglomerates and single-segment firms in terms of analyst forecast error and number of all analysts following the firm is even wider, at roughly 25% in favor of conglomerates, but even a simple size-adjustment (results available upon request) turns those spreads in single-segment firms' favor, and controlling for other determinants of dependent variables in Panels B and C (firm age, return volatility, etc.) produces univocal evidence that conglomerates and especially high-complexity conglomerates operate in a worse information environment than comparable single-segment firms.

4 Anomalies for Conglomerates and Single-Segment Firms

4.1 Defining the Anomalies

The current section compares the strength of four prominent anomalies for conglomerates and single-segment firms. The first anomaly, the turnover variability effect of Chordia et al. (2001), refers to the puzzling negative cross-sectional relation between coefficient of variation (standard deviation over average) of monthly turnover, measured in the past 36 months, and future returns. Taken at the face value, the relation suggests that investors pay a premium for holding stocks prone to trading activity drying up. Chordia et al. argue that extremely variable trading activity presents a risk of not being able to unload the stocks in the day of one's choice, and thus the relation between turnover variability and future returns should have been positive, not negative.

The second anomaly is the analyst disagreement effect of Diether et al. (2002), who find a similar negative cross-sectional relation between future returns and dispersion of analyst earnings forecasts (scaled by absolute value of the consensus forecast). Diether et al. ascribe the negative relation not to the tendency of investors to pay a premium for stocks, about which analysts disagree, but to overvaluation of high-disagreement stocks due to short-sale constraints, as in Miller (1977). Miller suggests that short-sale constraints make stocks overpriced by keeping pessimistic investors out of the market. This form of overpricing is naturally stronger for firms about which investors disagree more, since for such firms the negative views of pessimists, who are kept out of the market, are likely to be more extreme.

The third anomaly, the idiosyncratic volatility effect of Ang et al. (2006), is similar in spirit and probable cause to the analyst disagreement effect and refers to the negative cross-sectional relation between idiosyncratic volatility of stock returns and average returns going forward.

The fourth anomaly covered in this paper is the turnover effect of Datar et al. (1998), who find that presumably more liquid firms with higher turnover (shares traded within a month over shares outstanding) have lower returns going forward.

The fifth and sixth anomalies in this paper are the investment growth effect of Anderson and Garcia-Feijoo (2006) and the asset growth effect of Cooper et al. (2008), which refer to the negative cross-sectional relation between annual investment/total assets growth rate and future alphas. The anomalies are strong in the three-factor Fama-French alphas, but the investment factor (based ion investment-to-asset ratio) in the five-factor model handles both anomalies well in the full sample. However, further analysis shows that the anomalies persist for conglomerates (complex conglomerates) even in the five-factor alphas.

The seventh anomaly is the cumulative issuance puzzle of Daniel and Titman (2006), which records that routine equity retirers beat routine equity issuers on risk-adjusted basis.

The last, eighth anomaly is the retained earnings effect of Ball et al. (2020), who find that firms with higher ratio of retained earnings to market value earn larger future alphas. Ball et al. (2020) also argue that the retained earnings effect overlaps with the value effect and the difference between book-to-market and retained-earnings-to-market is not priced. Consistent with that, in the full sample, the retained earnings effect is strong in the CAPM alphas, but weak in the three-factor alphas and even weaker in the five-factor alphas, but further analysis finds it still strong for more complex conglomerates.

4.2 Portfolio Sorts

The evidence in Table 1 shows that higher firm complexity causes institutional investors and analysts to abandon firms. Some potential reasons for that highlighted by Table

1 are lower earnings quality and higher analyst forecast errors for more complex firms, but complexity itself is likely to be the deeper variable that unites all evidence in Table 1. Complex firms are harder to understand, figuring out their true value and future cash flows requires more expertise and more resources, and that leads both to sophisticated investors and information producers abandoning such firms and to worse quality of earnings numbers and forecasts. This observation motivates using firm complexity as a limits to arbitrage proxy: it is more costly and dangerous to trade against anomalies in the sample of more complex firms and a smaller number of sophisticated investors find it worthwhile to do so, hence anomalies will be stronger for more complex firms.

Panel A of Table 2 looks at the turnover variability effect of Chordia et al. (2001): the top row of Panel A's left part confirms that the turnover variability effect survives in the more recent sample (1978-2018) and exists even in the five-factor Fama and French (2015) model alphas: the alpha spread between the lowest and highest quintiles stands at 21 bp per month, t-statistic 1.85 and comes exclusively from the negative alpha of the top quintile.

The next two rows of Panel A split the sample into single-segment firms and conglomerates (using the full-sample breakpoints to allocate firms into turnover variability quintiles) and find that for single-segment firms the low-minus-high alpha spread, as well as the negative alpha of the top quintile, are within 10 bp of zero, while for conglomerates both alphas more than double compared to the full sample and become significant at the 5% level: the low-minus high alpha spread in the conglomerate-only sample checks in at 44 bp, t-statistic 2.1, and the negative alpha of the top turnover variability quintile is at -46 bp per month, t-statistic -2.31.

The last row of Panel A1 presents the difference in the alphas in the second and third row (among single-segment firms and conglomerates). The 35 bp per month difference in turnover variability effect between single-segment firms and conglomerates is insignificant with t-statistic of 1.54, but the difference in the alphas of the top quintile is even larger at 48 bp per month and has the t-statistic of 2.5.

Panel B1 repeats the analysis for the analyst disagreement effect of Diether et al. (2002): in the five-factor alphas, the effect is at 34 bp per month, t-statistic 2.35, in the sample of all firms, close to that (28 bp per month) for single-segment firms and roughly double that (63 bp per month) for conglomerates. It is also interesting that while the effect is exclusively driven by the highest disagreement quintile for all firms and conglomerates, for single-segment firms the alpha of the top disagreement quintile is effectively zero, and the disagreement effect for single-segment firms is all on the long side, which is inconsistent with the Miller (1977) mechanism.

The bottom row of Panel B1, similar to Panel A1, finds that the difference in the disagreement effect between single-segment firms and conglomerates is marginally significant at 35 bp per month, while the difference in the top quintile alphas is larger and more significant (48 bp per month, t-statistic 2.56).

Panel C1 looks at the idiosyncratic volatility effect of Ang et al. (2006) and arrives at similar results: the idiosyncratic volatility effect is alive and well in the five-factor alphas if we look at the full sample and is exclusively driven by the negative alpha of the top idiosyncratic volatility quintile. In the subsample of single-segment firms, the sorts on idiosyncratic volatility produce no significant alphas, including the low-minus-high alpha spread, whereas in the subsample of conglomerates both the low-minus-high alpha spread and the alpha of the top idiosyncratic volatility quintile are significant and both are higher than in the full sample. The difference in those two alphas between conglomerates and single-segment firms lacks statistical significance, but stands at 30 bp per month, which implies that while we cannot formally reject that the idiosyncratic volatility effect is stronger for conglomerates than for single-segment firms, we also cannot reject that the said difference in the idiosyncratic volatility effect stands at, e.g., 70 bp per month.

Panel D1 considers the turnover effect of Datar et al. (1998) and finds that while the turnover effect is not significant in the five-factor alphas, there is a large and significant difference between turnover sorts for single-segment firms and conglomerates. For single-segment firms, the turnover effect is "backwards" compared to the original Datar et al. result: high-turnover single-segment firms have positive alphas, which exceed the alphas of low-turnover firms by 28 bp per month. For conglomerates, the turnover effect is back to its original strength of roughly 40 bp per month even after controlling for the additional Fama-French factors, and the alpha of high-turnover conglomerates, -25 bp per month, is significant at 10% level.

Lastly, the right side of Table 2 (Panels A2-D2) looks at the spread in sorting variables across the quintiles for the different samples in Panels A1-D1. Volatility measures, such as idiosyncratic volatility and turnover variability, are strongly negatively related to firm size, while turnover is strongly positively related to size. Since Panel A of Table 1 shows that conglomerates are, on average, 2.5 times larger than single-segment firms, it is possible that the spread in the sorting variables is different in the conglomerate sample. This concern is to some extent alleviated by the fact that I use the same full-sample breakpoints to assign firms to, say, top turnover quintile in the single-segment and conglomerate subsamples, but it is still possible that the conglomerates include more firms with extremely high turnover, and thus average turnover in the top turnover quintile will be larger in the conglomerate subsample, making the turnover effect in this subsample mechanically larger.

Panels A2-D2 do not reveal much of the said difference. The difference in the spread of the sorting variable between top and bottom quintile is different by less than 10% as one compares the single-segment and conglomerate subsamples, and in the case of turnover variability it is only 1%. The difference in the median sorting variable in the top quintile, which drives the anomalies, is even smaller and never exceeds 6%.

Panels E1 and F1 look, respectively, at sorts on investment growth, as in Anderson and Garcia-Feijoo (2006), and asset growth, as in Cooper et al. (2008). The top rows show that in the full sample the effects do not exist in the five-factor alphas, which is not surprising given their proximity to the investment factor (CMA), which is based on investment-to-asset ratio. The asset growth effect in the five-factor alphas even becomes weakly negative (high asset growth firms have positive alphas). The same is true about the single-segment subsample.

However, in the conglomerates subsample the investment growth effect becomes significant even in the five-factor alphas that control for CMA - the alpha spread between low and high investment growth firms is at 45 bp per month, t-statistic 2.63. The alpha spread is primarily driven by the negative alphas of high-growth companies, which sits at -37 bp per month, and the difference between the investment growth effect for conglomerates and single-segment firms is estimated at 32.5 bp per month, significant at the 10% level. The difference in asset growth effect between conglomerates and single-segment firms, recorded in Panel F1, is similar in magnitude, but lacks statistical significance. However, the statistical significance is there for the main driver of the asset growth effect, the alpha of the highest asset growth quintile, which is -26 bp per month, t-statistic -2.3 for conglomerates, full 50 bp more negative than for single-segment firms (t-statistic for the difference -3.52).

Panel E2 and F2 look at the spread in investment/asset growth in the investment/asset growth sorts, both in the full sample and separately for single-segment firms and conglomerates. The difference in the spread between single-segment firms and conglomerates works against finding that the investment/asset growth effects are stronger for conglomerates: the difference in the growth rates of assets/capital expenditures between the lowest and highest growth quintiles is 20%/15% larger for single-segment firms.

Panel G1 considers the cumulative issuance puzzle of Daniel and Titman (2006), which is highly significant at 32 bp per month in the full sample. Further analysis reveals, however, that the cumulative issuance puzzle comes exclusively from the conglomerates subsample, where is stands at 71 bp per month, t-statistic 4.06, whereas for single-segment firms the cumulative issuance puzzle is estimated to be insignificant 13 bp per month (the difference between the two estimates is significant with t-statistic 2.61). Similar difference is observed for the negative alpha of the top cumulative issuance quintile (routine equity issuers), which is where (almost) all of the cumulative issuance puzzle is coming from. Panel G2 tabulates median cumulative issuance across quintiles for the full sample and the two subsamples and finds no difference between single-segment firms and conglomerates in terms of the spread in cumulative issuance.

Lastly, Panel H1 looks at the retained earnings effect of Ball et al. (2020), which is insignificant in five-factor alphas in the full sample and for single-segment firms, but significant at 10% level for conglomerates, and the difference in the retained earnings effect between single-segment firms and conglomerates is also significant with t-statistic 2.28. Panel H2 looks at retained earnings to market ratio across retained earnings to market quintile and finds that conglomerates and single-segment firms subsamples are similar in this regard, and thus the stronger retained earnings effect for conglomerates in Panel H1 is unlikely to be mechanical.

4.3 Cross-Sectional Regressions

The main conclusion of Table 2 is that firm complexity (more precisely, the status of the firm as a conglomerate or not) is a good limits to arbitrage variable and several anomalies are therefore stronger for conglomerates than single-segment firms despite conglomerates being 2.5 times larger and significantly more liquid. The lack of control for size and liquidity of conglomerates is working against this hypothesis in Table 2; on the other hand, other confounding effects can still be uncontrolled for. For example, Stambaugh et al. (2015) find that the interaction of their composite overpricing measure and idiosyncratic volatility provides the strongest to date explanation of the idiosyncratic volatility effect of Ang et al. (2006). The logic of Stambaugh et al. that overpriced firms are even more overpriced if idiosyncratic volatility is higher is also likely to apply to analyst disagreement and potentially turnover (e.g., Lee and Swaminathan, 2000, find that momentum effect is stronger for high turnover firms, and high turnover losers are particularly overpriced).

In the cross-sectional Fama-MacBeth (1973) regressions in Table 3, I use the standard asset pricing controls (size, market-to-book, profitability, investment-to-assets, momentum, short-term reversal), as well as the composite overpricing measure of Stambaugh et al. (2015) and its interaction with either of the four anomaly variables (turnover variability in Panel A, analyst disagreement in Panel B, idiosyncratic volatility in Panel C, turnover in Panel D). The main variables of interest are the anomaly variable itself and its interaction with alternative complexity measures (which serve as names of columns in Table 3 panels). The complexity variables themselves are also controlled for.

Panel A of Table 3 studies the turnover variability effect of Chordia et al. (2001) and its cross-section. Similar to the evidence in Stambaugh et al. (2015) on the interaction of their composite overpricing measure and the idiosyncratic volatility effect of Ang et al. (2006), Panel A finds that the turnover variability effect is significantly stronger for overpriced firms, and flips its sign for underpriced companies. More importantly, the last row of the panel looks at the interaction between turnover variability and the conglomerate dummy, as well as several other complexity measures discussed above. All complexity measures confirm that the turnover variability effect is significantly stronger for higher complexity firms, in particular conglomerates.[2]

Panel B looks at the analyst disagreement effect of Diether et al. (2002), which does not seem to interact significantly with the Stambaugh et al. measure, even though the point estimates of the interaction are negative and controlling for the interaction makes the slope on the disagreement variable insignificantly positive rather than negative. The interaction of disagreement with complexity also has the predicted sign, but lacks significance for simpler complexity measures like the conglomerate dummy, number of segments and 1-HHI, but the significance of the interaction of disagreement and complexity is restored when I look at measures of segment diversity (RSZ, CV_{OL}, CV_{SGA}).

The results in Panel C that considers the idiosyncratic volatility effect of Ang et al. (2006) fall close to the results in Panel A, with both interaction terms consistently significant, and the results in Panel D that looks at the turnover effect of Datar et al. (1998) are more similar to the results in Panel B, with the interaction of turnover and complexity consistently maintaining the predicted sign across complexity measures, but becoming statistically significant only if measures of segment diversity are used.

Asset growth and cumulative issuance are parts of the Stambaugh et al. overpricing measure, so I decide against using the Stambaugh measure and its interaction with anomaly variables as additional controls in Panels E-H, which deal with asset growth effect, the cumulative issuance puzzle and the two other potentially related anomalies. Instead, I use institutional ownership and its interaction with the anomaly variables. Panels G and H show that the cumulative issuance puzzle and the retained earnings effect are significantly stronger when institutional ownership is low and absent if it is high. Panel F finds the same for the asset growth effect, even though the interaction between asset growth and

[2] Several known predictors of returns, such as momentum, investment, and profitability are insignificant in the presence of the Stambaugh et al. composite overpricing measure, because this measure includes (ranks of) those variables in addition to several others like accruals, net issuance, and distress. The significance of those predictors is restored if I drop the Stambaugh et al. measure.

institutional ownership is significant only at 10% level.

Turning to the interaction between the anomalies and complexity, I find that the interaction between investment/asset growth and complexity in Panel E/F is reliably negative irrespective of what measure of complexity I use. The same is true for the interaction of cumulative issuance and complexity in Panel G, though the interaction between cumulative issuance and the conglomerate dummy (Cong) or 1-HHI is significant only at 10% level, and the interaction between cumulative issuance and number of segments (NSeg) or segment diversity in terms of (imputed) SG&A-to-asset ratio CV_{SGA} is marginally significant at 5% level. Lastly, in Panel H, which looks at the retained earnings effect, the interaction of complexity and retained earnings to market ratio is significant irrespective of the complexity measure used. In all cases, the interaction terms in the last row of Panels E-H suggest that the anomalies are stronger for conglomerates and in particular more complex conglomerates.

Overall, the results in Table 3 corroborate the results in Table 2 using a different research design and confirm that the anomalies studies in the paper are stronger for conglomerates than for single-segment firms. The results of Table 3 also suggest that continuous complexity measures can fare even better than the conglomerate dummy in relating the strength of the anomalies to firm complexity, which will be the topic of the next section.

5 Anomalies for High- and Low-Complexity Conglomerates

5.1 Portfolio Sorts

Panels B and C of Table 1 suggest that firm complexity affects information environment in a more material way than a simple "zero-one" distinction between single-segment firms and conglomerates: in the conglomerates-only subsample (Panel C) firm complexity is still negatively related to analyst following and institutional ownership. Motivated by this relation, Table 4 performs independent double sorts on the four anomaly variables. The sorts on the anomaly variables are the same quintile sorts as in Table 2; the complexity sorts split firms into three groups - single-segment firms (zero complexity), conglomerates with the complexity variable below median (low complexity) and conglomerates with the complexity variable below median (high complexity). The complexity variable used is the sorts is the RSZ measure of market-to-book diversity between segments; the results are qualitatively the same when I use other complexity variables such as segment diversity in terms of operating leverage (CV_{OL}) or sales-based *1-HHI* measure.

Panel A looks at the turnover variability effect of Chordia et al. (2001) and finds that the effect is coming exclusively from high-complexity conglomerates. Panel A of Table 2 that splits the sample into single-segment firms and conglomerates, without differentiating between conglomerates of low and high complexity, records the turnover variability effect for all conglomerates at 63 bp per month, t-statistic 3.47. Panel A of Table 4 finds that the turnover variability effect for low-complexity conglomerates is only 22 bp per month, t-statistic 1.09, while for high-complexity conglomerates it stands at 91 bp per month, t-statistic 2.40.[3]

The last two rows of Panel A test whether the difference in the turnover variability effect between high-complexity conglomerates and either single-segment firms or low-complexity conglomerates is significantly different from zero and finds that it is in both cases. The source of the difference is the top turnover variability quintile; in the last row of Panel A (the comparison of low- and high-complexity conglomerates) the alphas of the bottom three quintiles are effectively zero, and the alpha of the fourth quintile is marginally significant.

[3]The figures for single-segment firms are somewhat different in Tables 2 and 4, because the data needed to compute the RSZ measure are not available in the first few years of the sample.

Panel B (the disagreement effect of Diether et al., 2002) and Panel D (the turnover effect of Datar et al., 1998) present very similar evidence. Both the disagreement effect and the turnover effect are present only for high-complexity conglomerates, and the difference with low-complexity conglomerates is significant in Panel B.

In Panel C, the idiosyncratic volatility effect of Ang et al. (2006) is significant for both low- and high-complexity conglomerates, but the difference is still 20 bp in favor of the latter, and the difference between the alphas of the top idiosyncratic volatility quintile, which creates almost the whole anomaly, is even larger at 34 bp per month.

Panel E (the investment growth effect) presents the only exception to the rule that anomalies are stronger for high-complexity conglomerates: the investment growth effect is very similar in both complexity groups.

Panels F-H present strong evidence that the asset growth effect, the cumulative issuance puzzle, and the retained earnings effect are driven exclusively by conglomerates of above-median complexity. For such conglomerates, the aforementioned anomalies are significant at 44-81 bp per month, with t-statistics of at least 2.42. For low-complexity conglomerates, on the other hand, the three anomalies in Panels F-H are statistically insignificant. The difference in the strength of anomalies between high- and low-complexity conglomerates is statistically significant in Panels F and G, and still at 40.5 bp per month, t-statistic 1.54 in Panel H.

The overall impression from Table 4 is that the degree of firm complexity matters and anomalies are stronger for more complex conglomerates despite those conglomerates being more liquid (see Panel A of Table 1). The split into two groups can seem crude, but finer sorts are not feasible, since the Compustat segments database covers only a subset of Compustat firms, and conglomerate are roughly 30% of this reduced population. Even in the current split, where these 30% are split into two complexity groups and five anomaly quintiles, the resulting portfolios have, on average, 3% of firms on Compustat segments, and some portfolios have less than 2%.

5.2 Cross-Sectional Regressions

Table 5 attempts to establish a finer distinction between low- and high-complexity conglomerates by re-running cross-sectional Fama-MacBeth (1973) regressions from Table 3 in the conglomerates-only subsample. Panel A explores the link between conglomerate's complexity and the turnover variability effect of Chordia et al. (2001) and finds that this link is visible for four complexity measures out of five, even though the interaction between complexity and turnover variability is significant only at the 10% level for three complexity measures. The reduction in significance is to be expected though, since the sample size is reduced in most years by a factor of three compared to Table 3, and even the interaction between turnover variability and the Stambaugh et al. overpricing measure, which used to be strongly significant in Table 3, loses significance in Panel A of Table 5 in three out of five cases. It is also important that for three out of five complexity measures the slope on the their interaction with turnover variability actually slightly increases compared to Panel A of Table 3, so the loss of significance in most cases is the loss of power rather than the decline of the effects' magnitude.

In Panel B that looks at the analyst disagreement effect of Diether et al. (2002), I find, as in Panel B of Table 3, that only measures of segment diversity matter for the strength of the analyst disagreement effect. The coefficient on interaction of analyst disagreement with one out of the three segment diversity measures, CV_{SGA}, loses significance (the t-statistic drops to -1.56), but the coefficients on all three interaction terms with segment diversity measures (RSZ, CV_{OL}, CV_{SGA}) roughly double compared to Panel A of Table 3 instead of declining.

Panel C (the idiosyncratic volatility effect of Ang et al., 2006) is the only panel of Table 5 where the interaction term with complexity is insignificant across all complexity measures and sometimes turns positive rather than negative (in the three other panels, the point estimates are always negative, indicating stronger anomaly for more complex conglomerates, even when the coefficients are not significant).

Panel D (the turnover effect of Datar et al., 1998) produces the strongest evidence in Table 5 of the positive link between the strength of an anomaly and firm complexity: three of the interaction terms are significant at the 1% level and one more is significant at the 10% level. The coefficients on all interaction terms, including the insignificant one, increase roughly twofold compared to Panel D of Table 3, and this increase indicates a better fit after the problem of the large mass at zero was resolved for the complexity measures.

Panels E and F look at the investment growth and asset growth effects (from Anderson and Garcia-Feijoo, 2006, and Cooper et al., 2008, respectively) and finds that nine of out of ten interaction terms between asset/investment growth and various complexity measures come out negative (indicating stronger anomaly for more complex conglomerates), with five out of the nine being statistically significant (one more coefficient on the interaction term has t-statistic of -1.80, and the only positive coefficient is insignificant). Similar to Panels A-D, the interaction with segment diversity measures tends to be more significant than the interaction with NSeg or 1-HHI.

In Panel G (the cumulative issuance puzzle of Daniel and Titman, 2006), all five measures of complexity reveal that more complex conglomerates have stronger cumulative issuance puzzle - for two of complexity measures, the relation is significant at the 1% level, and for two more it is significant at the 10% level.

Finally, Panel H looks at the retained earnings effect and finds that its strength is largely unrelated to NSeg and 1-HHI, but the retained earnings effect seems stronger for firms with greater earnings diversity.

Overall, Table 5 supports the conclusion of Table 4 that higher-complexity conglomerates have stronger anomalies despite higher-complexity conglomerates being more liquid. Going across complexity measures, it seems that the crude NSeg measure that simply counts the segments does the worst as a predictor of anomalies' cross-sectional strength (though NSeg is also more strongly related to size and liquidity in a way that would make anomalies weaker for high-NSeg firms). Sales concentration (*1-HHI*) is the second-weakest complexity measure, and the three measures based on segment diversity in terms of market-to-book or operating leverage are the strongest cross-sectional predictors of the four anomalies' strength.

6 Conclusion

The paper shows that anomalies are stronger for higher-complexity firms. Eight well-known anomalies, including the analyst disagreement effect of Diether et al. (2002), the idiosyncratic volatility effect of Ang et al. (2006), and the asset growth effect of Cooper et al. (2008), and the cumulative issuance puzzle of Daniel and Titman (2006), are used as examples. The anomalies are stronger for conglomerates than for single-segment firms, despite conglomerates being, on average, 2.5 times larger and significantly more liquid. The anomalies are also stronger for high-complexity conglomerates (e.g., ones with business segments more diverse in terms of market-to-book or operating leverage) than for low-complexity conglomerates.

Firm complexity can be thought of as a limits to arbitrage variable. Conglomerates are harder to understand and more costly to analyze: in order to arrive at their fair value, one has to have expertise in all industries the conglomerate operates in, one has to resolve the issue of assigning the overhead properly to different divisions from industries with different operating leverage, and one also have to estimate how the benefits of conglomeration (coinsurance, synergies) will change relative to the costs (inefficient investment and suboptimal between-segments transfers, inter-division politics).

The analysis of conglomerates' information environment supports the hypothesis that conglomerates are harder to analyze: holding other relevant firm characteristics, including firm size, fixed, conglomerates have less analyst following than single-segment firms and this following is of worse quality: analysts produce larger earnings forecast errors and a smaller number of them are industry specialists. Conglomerates also have, *ceteris paribus*, lower institutional ownership and lower earnings quality than single-segment firms. These conclusions also hold when I compare low- and high-complexity conglomerates.

An attractive feature of firm complexity as a limits to arbitrage variable is that it guides arbitrageurs to trading relatively large and liquid firms, whereas the vast majority of existing limits to arbitrage variables suggest that anomalies are stronger for small, illiquid, highly volatile firms, an observation of limited practical importance. From the academic standpoint, stronger anomalies for more complex firms are more likely to violate market efficiency than stronger anomalies for small, illiquid, highly volatile firms.

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A Data Appendix

AG (asset growth) - annual change in total assets (*at* item from the Compustat annual file) divided by preceding year's value of total assets.

Age (firm age) - number of months since the firm first appeared on the CRSP monthly file.

Amihud (Amihud price impact measure) - the average ratio of absolute return to dollar volume, both from CRSP. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and the stock price of less than $5 at the end of the previous year are excluded).

 # An (number of analysts; analyst coverage) - the number of analysts covering the firm (from the IBES summary file).

Beta (market beta) - from the CAPM regression estimated separately for each firm using monthly returns from the past 36 months.

BLev (book leverage) - total liabilities (*lt* item from the Compustat annual file) divided by total assets (*at* item).

Cong (conglomerate dummy) - 1 if the firm is a conglomerate, 0 otherwise. The firm is a conglomerate if it has business segments in more than one two-digit SIC industry.

CumIss (cumulative issuance) - the difference between the log market capitalization growth and the log cumulative returns (both calculated from CRSP monthly file) in the past five years.

CV OL, $\boldsymbol{CV_{OL}}$ - standard deviation of imputed segment-level operating leverage divided by the weighted average imputed operating leverage of all segments. Segment-level assets (*ias* item on the Compustat segment file) are used to determine the weights used to compute the standard deviation and the weighted average. Imputed operating leverage for a segment is average operating leverage of all single-segment firms with the same two-digit SIC code. Operating leverage is costs of goods sold (*cogs* item from the Compustat annual file) plus sales, general, and administrative expenses, SG&A (*xsga* item) divided by total assets (*at* item).

CV SGA, $\boldsymbol{CV_{SGA}}$ - standard deviation of imputed segment-level SG&A-over-assets ratio divided by the weighted average imputed SG&A-over-assets ratios of all segments. Segment-level assets (*ias* item on the Compustat segment file) are used to determine the weights used to compute the standard deviation and the weighted average. Imputed SG&A-over-assets ratio for a segment is average SG&A-over-assets ratio of all single-segment firms with the same two-digit SIC code.

CVT (turnover variability) - coefficient of variation (standard deviation over the average) of monthly turnover measured between months t-2 and t-36. Turnover is dollar volume over market cap, both dollar volume and market cap are from CRSP.

Disp (analyst forecast dispersion) - standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the outstanding earnings forecast (zero-mean forecasts and forecasts by only one analyst are excluded). Earnings forecasts are from the IBES summary file.

Div (dividend yield) - dividends (*dv* from the Compustat annual file) divided by the product of shares outstanding (*csho* item) and end-of-fiscal-year share price (*prcc_f* item).

EarnQ (earnings quality) - coefficient of variation (standard deviation over average) of discretionary accruals from Dechow et al. (1995). Coefficient of variation is calculated using discretionary accruals in quarters t-1 and t-8. Discretionary accruals (DA) are from the modified Jones (1991) model

$$DA_t = \frac{Acc_t}{atq_{t-1}} - a_1 \cdot \frac{1}{atq_{t-1}} - a_2 \cdot \frac{\Delta saleq_t - \Delta rectq_t}{atq_{t-1}} - a_3 \cdot \frac{ppegtq_t}{atq_{t-1}} \quad \text{(A-1)}$$

where *atq* is total assets, *saleq* is total quarterly revenue, *rectq* is receivables, and *ppegtq* is gross PPE (plant, property, and equipment), all from the Compustat quarterly file. The coefficients a_1, a_2, a_3 come from cross-sectional regression, performed separately each quarter using all Compustat quarterly firms, of accruals (Acc) on the variables above with change in receivables omitted:

$$\frac{Acc_t}{atq_{t-1}} = a_1 \cdot \frac{1}{atq_{t-1}} + a_2 \cdot \frac{\Delta saleq_t}{atq_{t-1}} + a_3 \cdot \frac{ppegtq_t}{atq_{t-1}} \quad \text{(A-2)}$$

Accruals are defined as change in current assets (item *actq*) minus change in cash (item *cheq*) minus change in current liabilities (item *lctq*) plus change in short-term debt (item *dlcq*) plus change in taxes payable (item *txpq*) minus depreciation (item *dpq*).

EffTick (effective tick size) - measure of effective bid-ask spread from Holden (2009). On the simple $\$\frac{1}{8}$ grid, frequency of odd $\frac{1}{8}$s prices (prices that end with $\frac{1}{8}$, $\frac{3}{8}$, $\frac{5}{8}$, or $\frac{7}{8}$) measures the probability of the bid-ask spread being equal to $\$\frac{1}{8}$, the frequency of odd $\frac{1}{4}$s prices measures the probability of the bid-ask spread being equal to $\$\frac{1}{4}$, the frequency of the prices that end $\frac{1}{2}$ measures the probability of the bid-ask spread being $\$\frac{1}{2}$, and the frequency of whole-dollar prices measures the probability of the spread being \$1. For each firm-month, I estimate the probabilities of the spread as above and compute its expected value by multiplying the probabilities by the respective spread values. Following Holden (2009), I use the $\$\frac{1}{16}$ grid before 2001 (decimalization) and the grid with clustering on dollars, half-dollars, quarters, dimes, nickels, and cents from 2001 on.

Error (analyst forecast error) - the absolute value of the difference between the one-year-ahead consensus forecast and actual earnings divided by actual earnings. All variables are from the IBES summary file.

1-HHI **(sales-based complexity)** - where HHI is the Herfindahl index computed using segment sales, $HHI = \sum_{N}^{i=1} s_i$. N is the number of segments (from the Compustat segment file, segments with the same two-digits SIC code are counted as one segment), s_i is the fraction of total sales generated by segment i.

IG (investment growth) - annual change in capital expenditures (capx item from the annual Compustat file) divided by preceding year's value of capital expenditures.

Intan (intangible assets) - intangible assets (*intan* item from the annual Compustat file divided by total assets (*at* item).

Inv (investment-to-assets) - annual change in capital expenditures (capx item from the annual Compustat file) divided by total assets (at item from Compustat) in the preceding year.

IO (institutional ownership) - sum of institutional holdings from Thomson Financial 13F database, divided by shares outstanding from CRSP. All stocks below the 20th NYSE/AMEX size percentile are dropped. If the stock is not dropped, appears on CRSP, but not on Thomson Financial 13Fs, it is assumed to have zero IO.

IVol (idiosyncratic volatility) - standard deviation of residuals from the three-factor Fama and French (1993) model, fitted to daily data for each firm-month (at least 15 valid observations are required).

Loss (Loss dummy) - 1 if the company incurred an operating loss in the immediate quarter (*epspiq* item from the Compustat quarterly file is negative), 0 otherwise.

MB (market-to-book) - equity value (*csho* item times *prcc_f* item) divided by book equity (*ceq* item) plus deferred taxes if available (*txdb* item), all items from the Compustat annual file.

MLev (market leverage) - long-term debt (*dltt*) plus short-term debt (*dlc*) divided by equity value (*prcc_f* times *csho*), all items from the Compustat annual file.

Mom (cumulative past return) - cumulative monthly return to the stock between month t-2 and t-12, monthly returns are from CRSP.

Nasdaq (Nasdaq dummy) - 1 if the firm is a NASDAQ firm, 0 otherwise. A firm is classified as a NASDAQ firm if its CRSP events file listing indicator, *exchcd*, is equal to 3.

NSeg (number of segments) - number of business segments the firm has (from the Compustat segment file). Segments with the same two-digit SIC code are counted as one segment.

Over (Stambaugh et al. overpricing measure) - average percentage ranking from ranking firms on 11 priced characteristics (accruals, momentum, ROA, asset growth, gross profitability, investment-to-assets, net stock issuance, cumulative stock issuance, net operating assets, O-score, expected probability of bankruptcy) in a way that ranks the most overpriced firm (highest accruals or lowest momentum) as 100, the most underpriced firm as 1, and firms in between get a corresponding percentage rank (e.g., a firm ranked 50th most overpriced in a sample of 2000 will get a rank of 97.5). The average is taken for all firms with at least five rankings available, otherwise Over is set to missing. Detailed description of the process and the sorting variables is in Stambaugh, Yu, and Yuan (2015).

Price (stock price) - the stock price from the CRSP monthly file.

GProf (gross profitability) - total revenue (*sale*) minus cost of goods sold (*cogs*) divided by book value of equity (*ceq* plus *txdb*), all items from the Compustat annual file.

ROA (return on assets) - income before extraordinary items (*ib* item from Compustat annual) divided by total assets (*at* item from Compustat annual) in the previous year.

R&D (R&D-to-assets) - research-and-development expenditures (*xrd* item from Compustat annual) divided by total assets (*at* item from Compustat annual) in the previous year.

RetQ1 (return in the past quarter) - cumulative monthly return (from CRSP) in the past quarter.

RE (retained earnings over market) - retained earnings (*re* Compustat item) over market value of equity (*csho* times *prcc_f*). If accumulated other comprehensive income (*acominc* item) is available, it is deducted from retained earnings.

RetYR1/RetYR2 (return in the past year/two years ago) - cumulative monthly return (from CRSP) in the past year/in the year before that.

Rev (short term reversal) - stock return (from CRSP) in month t-1.

Roll (Roll measure) - effective bid-ask spread measure, computed within each firm-year as $Roll_t = 200 \cdot \sqrt{abs(Cov(R_t, R_{t-1}))}$, where R_t are daily stock returns from CRSP.

RSZ (RSZ complexity measure) - standard deviation of imputed segment-level market-to-book ratios divided by the weighted average imputed market-to-book ratios of all segments. Segment-level assets (*ias* item on the Compustat segment file) are used to determine the weights used to compute the standard deviation and the weighted average. Imputed market-to-book ratio for a segment is average market-to-book of all single-segment firms with the same two-digit SIC code.

S&P500 (S&P 500 dummy) - 1 for firms that are included in S&P500, 0 otherwise. S&P 500 firms have *spmim* variable equal to 10 in Compustat *sec_mth* file, .

 # Spec (number of specialists) - the number of analysts covering the firm who are specialists in the firm's industry. An analyst is considered a specialist in the firm's industry if he/she covers at least five other firms with the same two-digit SIC code in the same quarter. For a conglomerate, an analyst is classified as a specialist based on the industry affiliation of the largest segment. The data on firms each analyst covers is from the IBES detail file.

Spread - effective bid-ask spread implied by daily high and low prices. Spread is calculated as in Corwin and Schultz (2012):

$$\text{Spread} = \frac{2 \cdot (\exp^{\alpha} - 1)}{1 + \exp^{\alpha}}, \quad \text{where} \tag{A-3}$$

$$\alpha = \frac{\sqrt{\beta} \cdot (\sqrt{2} - 1)}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \quad \text{where} \tag{A-4}$$

$$\beta = \log^2\left(\frac{HI_t}{LO_t}\right) + \log^2\left(\frac{HI_{t+1}}{LO_{t+1}}\right) \quad \textit{and} \quad \gamma = \log^2\left(\frac{\max(HI_t,\ HI_{t+1})}{\min(LO_t,\ LO_{t+1})}\right) \tag{A-5}$$

Turn (turnover) - trading volume divided by shares outstanding (both from CRSP monthly data). The monthly turnover is then averaged in each calendar year with at least 5 valid observations. To make comparisons across exchanges more meaningful, I adjust NASDAQ volume for the double counting following Gao and Ritter (2010): NASDAQ volume is divided by 2 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and is unchanged after that. A firm is classified as a NASDAQ firm if its CRSP events file listing indicator (exchcd) is equal to 3.

TVol (total volatility) - volatility of monthly returns (from CRSP) measured in the past 24 months.

Zero (zero-volume/no-trade frequency) - the fraction of zero-return days within each firm-year.

Table 1. Firm Complexity and Information Environment

Panel A tabulates median size, median stock price, and median liquidity characteristics for single-segment firms and conglomerates, as well as low- and high-complexity conglomerates. Conglomerates are defined as firms with business segments in more than one industry, industries are defined using two-digit SIC codes. High-complexity conglomerates have CV_{OL} measure of diversity in segment-level imputed operating leverage above median. Liquidity measures include effective bid-ask spread measure (Spread) of Corwin and Schultz (2012), effective tick measure (Efftick) of Holden (2009), the Roll (1984) measure of effective bid-ask spread (Roll), the Amihud (2002) measure of price impact (Amihud), and the frequency of zero-return/no-trade days (Zero) from Lesmond et al. (1999).

Panels B and C present panel regressions of information environment proxies - log of number of analysts following the firm (# An), log of number of analysts that are specialists in the firm's (main) business (# Spec), institutional ownership (IO), log of absolute value of analyst forecast error (Error), and log of earnings quality (EarnQ) - on log of the firm complexity variable based on operating leverage (CV_{OL}) and the controls from the literature. Panel B looks at the full sample (firms in the Compustat segment file), Panel C restricts the sample to conglomerates only.

The controls in Panels B and C include the dummy variable for Nasdaq-traded stocks (Nasdaq), market beta (Beta), log of stock price (Price), log of stock turnover (Turn, dollar trading volume over market cap), log of 1 + total return volatility (TVol), the dummy variable for S&P 500 stocks (S&P500), log of 1 + firm market leverage (MLev) or book leverage (BLev), R&D expenditures over total assets (R&D), log of 1 + intangible assets over total assets (Intan), log of firm age (Age, the number of months since the firm first appeared on CRSP), dividend yield (Div), cumulative returns in the past quarter/year (RetQ1/RetYR1), return on assets (ROA), and quarterly dummy for negative net income (Loss). All independent variables, including complexity variables, are winsorized at 0.5% and 99.5%. Detailed definitions of all variables are in Data Appendix. The t-statistics use standard errors clustered by firm-year-quarter/month, depending on the frequency of the dependent variable. The sample period is from January 1978 to December 2018.

Panel A. Complexity and Information Environment

	Single	**Conglo**	**S-C**	**t-stat**	**LComp**	**HComp**	**H-L**	**t-stat**	**L-S**	**t-stat**
Size	189.6	479.1	-289.5	-8.77	511.8	475.5	-36.30	-1.80	322.2	6.92
Spread	1.297	0.715	0.581	15.3	0.715	0.693	-0.021	-3.62	-0.582	-15.7
Efftick	3.281	1.964	1.317	10.4	2.009	1.904	-0.104	-5.63	-1.272	-10.6
Roll	1.931	1.396	0.534	13.4	1.396	1.367	-0.029	-3.11	-0.534	-14.2
Amihud	0.406	0.102	0.304	6.91	0.112	0.090	-0.022	-5.34	-0.294	-6.92
Zero	0.171	0.129	0.042	8.72	0.130	0.125	-0.006	-5.91	-0.041	-8.34
Price	10.34	18.78	-8.440	-23.0	18.73	19.54	0.794	3.22	8.388	21.3

Panel B. Firm Complexity and Firm Information Environment: Full Sample

# An	1	# Spec	2	IO	3	EarnQ	4	Error	5
Const	0.524	**Const**	-0.624	**Const**	0.794	**Const**	1.660	**Const**	0.856
t-stat	*13.5*	**t-stat**	*-14.5*	**t-stat**	*30.5*	**t-stat**	*44.7*	**t-stat**	*21.1*
CV OL	-0.028	**CV OL**	-0.097	**CV OL**	-0.013	**CV OL**	0.038	**CV OL**	0.014
t-stat	*-5.22*	**t-stat**	*-14.5*	**t-stat**	*-3.93*	**t-stat**	*6.46*	**t-stat**	*4.61*
Beta	0.048	**Beta**	0.031	**Div**	-0.443	**SG**	-0.092	**BLev**	0.050
t-stat	*7.64*	**t-stat**	*5.10*	**t-stat**	*-3.48*	**t-stat**	*-9.99*	**t-stat**	*4.18*
Age	-0.154	**Age**	-0.045	**Age**	0.043	**Inv**	-0.085	**Intan**	-0.083
t-stat	*-27.4*	**t-stat**	*-7.66*	**t-stat**	*15.1*	**t-stat**	*-3.11*	**t-stat**	*-5.45*
MB	-0.055	**MB**	-0.078	**MB**	-0.022	**Age**	0.044	**Size**	-0.063
t-stat	*-7.90*	**t-stat**	*-10.0*	**t-stat**	*-5.38*	**t-stat**	*7.77*	**t-stat**	*-19.7*
Size	0.372	**Size**	0.357	**Size**	0.047	**MLev**	-0.019	**#An**	0.040
t-stat	*73.6*	**t-stat**	*54.3*	**t-stat**	*14.0*	**t-stat**	*-0.54*	**t-stat**	*5.98*
Price	0.062	**Price**	0.072	**Price**	0.065	**Size**	-0.021	**TVol**	0.306
t-stat	*6.71*	**t-stat**	*7.02*	**t-stat**	*13.4*	**t-stat**	*-6.23*	**t-stat**	*10.0*
Turn	0.921	**Turn**	2.070	**Turn**	0.936	**TVol**	-0.255	**Loss**	0.143
t-stat	*15.3*	**t-stat**	*31.0*	**t-stat**	*23.7*	**t-stat**	*-7.53*	**t-stat**	*20.0*
TVol	-0.120	**TVol**	0.059	**TVol**	-0.085	**Loss**	0.000	**R&D**	-0.081
t-stat	*-3.17*	**t-stat**	*1.64*	**t-stat**	*-11.8*	**t-stat**	*0.02*	**t-stat**	*-3.22*
Loss	-0.032	**Loss**	0.036	**Loss**	-0.011	**ROA**	0.023		
t-stat	*-4.88*	**t-stat**	*4.48*	**t-stat**	*-2.55*	**t-stat**	*0.98*		
Nasdaq	0.179	**Nasdaq**	0.134	**RetQ1**	-0.050				
t-stat	*12.1*	**t-stat**	*8.62*	**t-stat**	*-10.9*				
ROA	0.078	**ROA**	0.032	**RetYR1**	-0.029				
t-stat	*3.60*	**t-stat**	*1.41*	**t-stat**	*-13.2*				
RetYR1	-0.173	**RetYR1**	-0.149	**S&P500**	-0.109				
t-stat	*-25.3*	**t-stat**	*-20.9*	**t-stat**	*-8.49*				
RetYR2	-0.091	**RetYR2**	-0.099						
t-stat	*-18.2*	**t-stat**	*-18.8*						

Panel C. Firm Complexity and Firm Information Environment: Conglomerates Only

# An	1	# Spec	2	IO	3	EarnQ	4	Error	5
Const	0.462	**Const**	-0.757	**Const**	0.647	**Const**	1.732	**Const**	0.883
t-stat	*5.00*	**t-stat**	*-6.98*	**t-stat**	*14.2*	**t-stat**	*21.6*	**t-stat**	*10.1*
CV OL	-0.027	**CV OL**	-0.033	**CV OL**	-0.014	**CV OL**	0.018	**CV OL**	0.008
t-stat	*-2.69*	**t-stat**	*-2.78*	**t-stat**	*-2.21*	**t-stat**	*1.46*	**t-stat**	*1.32*
Beta	0.076	**Beta**	0.038	**Div**	-0.345	**SG**	-0.117	**BLev**	0.053
t-stat	*5.06*	**t-stat**	*2.10*	**t-stat**	*-3.09*	**t-stat**	*-4.98*	**t-stat**	*1.81*
Age	-0.153	**Age**	-0.049	**Age**	0.052	**Inv**	-0.117	**Intan**	-0.116
t-stat	*-12.3*	**t-stat**	*-3.38*	**t-stat**	*8.20*	**t-stat**	*-1.95*	**t-stat**	*-4.06*
MB	-0.108	**MB**	-0.110	**MB**	-0.007	**Age**	0.037	**Size**	-0.064
t-stat	*-6.54*	**t-stat**	*-5.35*	**t-stat**	*-0.85*	**t-stat**	*2.88*	**t-stat**	*-9.53*
Size	0.379	**Size**	0.345	**Size**	0.051	**MLev**	0.048	**# An**	0.047
t-stat	*40.0*	**t-stat**	*25.0*	**t-stat**	*8.33*	**t-stat**	*0.63*	**t-stat**	*3.37*
Price	0.034	**Price**	0.046	**Price**	0.051	**Size**	-0.016	**TVol**	0.280
t-stat	*1.51*	**t-stat**	*1.71*	**t-stat**	*5.03*	**t-stat**	*-2.34*	**t-stat**	*4.43*
Turn	0.137	**Turn**	2.365	**Turn**	1.037	**TVol**	-0.343	**Loss**	0.204
t-stat	*0.91*	**t-stat**	*15.0*	**t-stat**	*11.8*	**t-stat**	*-4.61*	**t-stat**	*13.3*
TVol	-0.104	**TVol**	-0.016	**TVol**	-0.061	**Loss**	0.018	**R&D**	-0.122
t-stat	*-1.16*	**t-stat**	*-0.17*	**t-stat**	*-5.13*	**t-stat**	*0.91*	**t-stat**	*-1.09*
Loss	-0.050	**Loss**	0.003	**Loss**	-0.019	**ROA**	0.103		
t-stat	*-3.52*	**t-stat**	*0.16*	**t-stat**	*-2.41*	**t-stat**	*1.29*		
Nasdaq	0.121	**Nasdaq**	0.127	**RetQ1**	-0.048				
t-stat	*3.92*	**t-stat**	*3.51*	**t-stat**	*-5.77*				
ROA	0.164	**ROA**	-0.117	**RetYR1**	-0.038				
t-stat	*1.90*	**t-stat**	*-1.25*	**t-stat**	*-8.63*				
RetYR1	-0.172	**RetYR1**	-0.153	**S&P500**	-0.135				
t-stat	*-12.3*	**t-stat**	*-9.73*	**t-stat**	*-6.56*				
RetYR2	-0.078	**RetYR2**	-0.102						
t-stat	*-7.90*	**t-stat**	*-8.90*						

Table 2. Anomalies for Conglomerates and Single-Segment Firms

The table presents quintile sorts on the variables indicated in the panels' headings. The left part of each panel shows five-factor Fama and French (2015) alphas of each quintile portfolio, while the right part tabulates median values of the sorting variables within each quintile. The alphas and medians are reported for the full sample (All row), only for singe-segment firms (SingleSeg row) and only for conglomerates (Conglos row). The last row of each panel (C-S) presents the difference in alphas/medians between single-segment and conglomerates subsamples. The sorts are performed using NYSE breakpoints. Stocks priced below $5 per share at the portfolio formation date are excluded from the sample. SingleSeg and Conglos rows use full-sample breakpoints. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2018.

Panel A. Turnover Variability Sorts

Panel A1. Five-Factor Alphas

	Low	**CVT2**	**CVT3**	**CVT4**	**High**	**L-H**
All	0.036	0.013	-0.040	-0.006	-0.176	0.212
t-stat	*1.04*	*0.23*	*-0.72*	*-0.07*	*-1.74*	*1.85*
SingleSeg	0.129	0.281	0.104	0.146	0.034	0.096
t-stat	*1.80*	*2.73*	*1.13*	*1.05*	*0.30*	*0.72*
Conglos	-0.021	-0.214	-0.242	-0.246	-0.462	0.442
t-stat	*-0.39*	*-2.37*	*-3.23*	*-2.52*	*-2.31*	*2.10*
C-S	-0.150	-0.495	-0.346	-0.392	-0.496	0.346
t-stat	*-1.53*	*-3.39*	*-2.85*	*-2.47*	*-2.50*	*1.54*

Panel A2. Median Turnover Variability

Spread	**Low**	**CVT2**	**CVT3**	**CVT4**	**High**	**H-L**
All	0.285	0.365	0.442	0.545	0.805	0.520
t-stat	*69.8*	*65.6*	*64.0*	*64.7*	*91.7*	*75.4*
SingleSeg	0.288	0.366	0.443	0.545	0.796	0.508
t-stat	*73.1*	*65.6*	*64.2*	*64.9*	*85.8*	*72.2*
Conglos	0.283	0.363	0.440	0.541	0.796	0.513
t-stat	*68.4*	*65.6*	*63.7*	*63.9*	*79.3*	*60.6*
C-S	-0.005	-0.003	-0.003	-0.004	0.000	0.005
t-stat	*-5.41*	*-6.36*	*-6.66*	*-6.29*	*0.14*	*1.80*

Panel B. Analyst Disagreement Sorts

Panel B1. Five-Factor Alphas

	Low	Disp2	Disp3	Disp4	High	L-H
All	0.062	-0.125	0.008	0.037	-0.274	0.336
t-stat	*1.11*	*-2.44*	*0.14*	*0.44*	*-2.26*	*2.35*
SingleSeg	0.254	0.156	0.091	0.251	-0.030	0.284
t-stat	*3.31*	*0.93*	*0.90*	*1.97*	*-0.22*	*2.02*
Conglos	0.118	-0.191	-0.021	0.020	-0.511	0.629
t-stat	*1.48*	*-1.26*	*-0.19*	*0.13*	*-3.37*	*3.47*
C-S	-0.136	-0.347	-0.112	-0.232	-0.482	0.346
t-stat	*-1.50*	*-1.78*	*-0.72*	*-1.51*	*-2.56*	*1.77*

Panel B2. Median Analyst Disagreement

	Low	Disp2	Disp3	Disp4	High	H-L
All	0.010	0.024	0.041	0.077	0.237	0.227
t-stat	*19.0*	*21.6*	*22.1*	*23.0*	*23.1*	*23.1*
SingleSeg	0.008	0.024	0.041	0.077	0.240	0.232
t-stat	*17.3*	*21.7*	*22.2*	*23.2*	*23.4*	*23.5*
Conglos	0.011	0.024	0.041	0.077	0.234	0.224
t-stat	*18.7*	*21.3*	*21.8*	*22.8*	*21.2*	*21.0*
C-S	0.003	0.000	0.000	-0.001	-0.006	-0.009
t-stat	*9.45*	*0.77*	*-0.24*	*-3.83*	*-1.67*	*-2.35*

Panel C. Idiosyncratic Volatility Sorts

Panel C1. Five-Factor Alphas

	Low	IVol2	IVol3	IVol4	High	L-H
All	0.045	-0.041	-0.200	-0.072	-0.292	0.337
t-stat	*0.99*	*-0.73*	*-2.72*	*-0.85*	*-2.30*	*2.20*
SingleSeg	0.102	0.125	-0.102	0.146	-0.089	0.192
t-stat	*1.01*	*1.30*	*-0.88*	*1.43*	*-0.63*	*0.96*
Conglo	0.135	-0.179	-0.280	-0.123	-0.362	0.497
t-stat	*1.49*	*-2.21*	*-2.78*	*-1.09*	*-2.32*	*2.58*
C-S	0.033	-0.303	-0.179	-0.269	-0.273	0.306
t-stat	*0.29*	*-2.62*	*-1.33*	*-1.82*	*-1.44*	*1.28*

Panel C2. Median Idiosyncratic Volatility

	Low	IVol2	IVol3	IVol4	High	H-L
All	0.008	0.011	0.015	0.019	0.031	0.023
t-stat	*40.6*	*40.4*	*42.0*	*43.7*	*42.7*	*42.4*
SingleSeg	0.008	0.011	0.015	0.019	0.031	0.023
t-stat	*39.7*	*40.5*	*42.1*	*43.8*	*42.9*	*42.8*
Conglo	0.008	0.011	0.015	0.019	0.029	0.021
t-stat	*40.7*	*40.3*	*42.1*	*43.2*	*43.6*	*43.4*
C-S	0.000	0.000	0.000	0.000	-0.002	-0.002
t-stat	*4.37*	*-5.95*	*-8.24*	*-9.83*	*-14.0*	*-15.1*

Panel D. Turnover Sorts

Panel D1. Five-Factor Alphas

	Low	Turn2	Turn3	Turn4	High	L-H
All	-0.056	-0.095	-0.111	-0.038	0.081	-0.137
t-stat	*-1.09*	*-1.72*	*-1.68*	*-0.64*	*0.90*	*-1.16*
SingleSeg	-0.035	-0.089	0.107	0.243	0.242	-0.277
t-stat	*-0.34*	*-0.91*	*1.07*	*2.84*	*2.05*	*-1.75*
Conglo	0.157	-0.160	-0.271	-0.050	-0.251	0.408
t-stat	*1.61*	*-2.06*	*-3.09*	*-0.56*	*-1.77*	*2.20*
C-S	0.192	-0.071	-0.378	-0.294	-0.494	0.685
t-stat	*1.23*	*-0.67*	*-2.97*	*-2.45*	*-2.84*	*2.90*

Panel D2. Median Turnover

	Low	Turn2	Turn3	Turn4	High	H-L
All	0.026	0.064	0.089	0.125	0.213	0.187
t-stat	*13.8*	*13.4*	*13.9*	*14.1*	*14.4*	*14.4*
SingleSeg	0.031	0.064	0.090	0.125	0.216	0.185
t-stat	*13.0*	*13.4*	*13.9*	*14.1*	*14.5*	*14.7*
Conglo	0.031	0.065	0.090	0.123	0.203	0.171
t-stat	*12.1*	*13.5*	*13.9*	*14.1*	*14.3*	*14.7*
C-S	0.001	0.000	0.000	-0.002	-0.013	-0.014
t-stat	*1.89*	*2.16*	*0.03*	*-5.23*	*-9.29*	*-9.12*

Panel E. Investment Growth Sorts

Panel E1. Five-Factor Alphas

	Low	IG2	IG3	IG4	High	L-H
All	0.073	-0.004	-0.012	0.017	-0.063	0.135
t-stat	*1.01*	*-0.06*	*-0.22*	*0.27*	*-0.72*	*1.16*
SingleSeg	0.205	0.228	0.223	0.111	0.082	0.123
t-stat	*2.00*	*2.49*	*2.51*	*1.15*	*0.84*	*1.02*
Conglos	0.074	0.003	-0.192	-0.129	-0.374	0.448
t-stat	*0.77*	*0.04*	*-2.48*	*-1.32*	*-2.99*	*2.63*
C-S	-0.131	-0.224	-0.414	-0.240	-0.456	0.325
t-stat	*-0.98*	*-1.74*	*-3.31*	*-1.69*	*-3.19*	*1.73*

Panel E2. Median Investment Growth

	Low	IG2	IG3	IG4	High	H-L
All	-0.406	-0.091	0.092	0.322	1.124	1.530
t-stat	*-44.1*	*-8.96*	*8.71*	*25.1*	*42.2*	*66.9*
SingleSeg	-0.422	-0.092	0.092	0.324	1.188	1.610
t-stat	*-45.9*	*-9.06*	*8.82*	*25.4*	*43.8*	*68.6*
Conglos	-0.378	-0.089	0.092	0.320	0.985	1.363
t-stat	*-41.1*	*-8.71*	*8.69*	*24.3*	*40.8*	*69.9*
C-S	0.043	0.003	0.000	-0.005	-0.203	-0.247
t-stat	*20.5*	*2.83*	*-0.32*	*-2.40*	*-17.8*	*-19.6*

Panel F. Asset Growth Sorts

Panel F1. Five-Factor Alphas

	Low	AG2	AG3	AG4	High	L-H
All	-0.047	-0.047	-0.025	0.133	0.096	-0.142
t-stat	*-0.65*	*-0.78*	*-0.43*	*2.22*	*1.35*	*-1.65*
SingleSeg	0.147	0.162	0.049	0.254	0.245	-0.098
t-stat	*1.47*	*1.72*	*0.50*	*2.49*	*2.69*	*-0.78*
Conglos	-0.072	-0.047	-0.084	0.017	-0.260	0.188
t-stat	*-0.81*	*-0.46*	*-1.04*	*0.19*	*-2.30*	*1.35*
C-S	-0.220	-0.209	-0.133	-0.237	-0.505	0.285
t-stat	*-1.57*	*-1.43*	*-1.13*	*-1.62*	*-3.52*	*1.44*

Panel F2. Median Asset Growth

	Low	AG2	AG3	AG4	High	L-H
All	-0.074	0.019	0.074	0.147	0.455	0.529
t-stat	*-15.1*	*5.53*	*22.3*	*36.0*	*27.2*	*30.7*
SingleSeg	-0.080	0.019	0.074	0.149	0.489	0.569
t-stat	*-15.8*	*5.45*	*22.5*	*35.9*	*24.8*	*27.8*
Conglos	-0.067	0.019	0.073	0.145	0.387	0.454
t-stat	*-14.7*	*5.59*	*22.1*	*36.5*	*32.3*	*37.0*
C-S	0.013	0.000	-0.001	-0.003	-0.102	-0.115
t-stat	*9.25*	*0.71*	*-4.03*	*-5.31*	*-10.0*	*-10.8*

Panel G. Cumulative Issuance Sorts

Panel G1. Five-Factor Alphas

	Low	CI2	CI3	CI4	High	L-H
All	0.032	-0.134	0.022	0.069	-0.283	0.316
t-stat	*0.41*	*-2.29*	*0.30*	*0.90*	*-4.04*	*3.29*
SingleSeg	0.047	-0.228	0.144	0.213	-0.081	0.128
t-stat	*0.48*	*-2.10*	*1.39*	*1.89*	*-0.92*	*0.89*
Conglos	0.094	-0.069	-0.033	-0.276	-0.612	0.706
t-stat	*0.76*	*-0.97*	*-0.34*	*-2.25*	*-4.48*	*4.16*
C-S	0.047	0.159	-0.177	-0.489	-0.530	0.577
t-stat	*0.33*	*1.31*	*-1.38*	*-2.86*	*-3.18*	*2.61*

Panel G2. Cumulative Issuance Growth

	Low	CI2	CI3	CI4	High	H-L
All	-0.328	-0.172	-0.069	0.052	0.363	0.691
t-stat	*-66.8*	*-39.6*	*-14.0*	*8.27*	*27.3*	*63.0*
SingleSeg	-0.332	-0.171	-0.068	0.054	0.369	0.701
t-stat	*-65.9*	*-39.3*	*-13.2*	*8.67*	*29.9*	*65.8*
Conglos	-0.327	-0.172	-0.070	0.046	0.352	0.679
t-stat	*-61.8*	*-39.7*	*-14.7*	*7.53*	*23.3*	*53.6*
C-S	0.006	-0.001	-0.002	-0.008	-0.017	-0.022
t-stat	*2.51*	*-1.20*	*-1.51*	*-10.0*	*-3.22*	*-4.46*

Panel H. Retained Earnings Sorts

Panel H1. Five-Factor Alphas

	Low	RE2	RE3	RE4	High	H-L
All	-0.097	-0.004	0.044	-0.049	-0.044	0.053
t-stat	*-0.90*	*-0.07*	*0.98*	*-0.75*	*-0.48*	*0.42*
SingleSeg	0.201	0.164	0.089	-0.062	0.063	-0.138
t-stat	*1.87*	*1.91*	*1.03*	*-0.66*	*0.54*	*-0.86*
Conglos	-0.443	-0.216	0.055	-0.010	-0.161	0.282
t-stat	*-3.28*	*-2.49*	*0.81*	*-0.12*	*-1.51*	*1.78*
C-S	-0.645	-0.380	-0.034	0.052	-0.224	0.420
t-stat	*-4.65*	*-2.98*	*-0.29*	*0.47*	*-1.74*	*2.28*

Panel H2. Retained Earnings Growth

	Low	RE2	RE3	RE4	High	H-L
All	-0.083	0.189	0.334	0.506	0.838	0.921
t-stat	*-4.18*	*13.4*	*20.8*	*25.4*	*29.4*	*42.0*
SingleSeg	-0.090	0.185	0.332	0.504	0.856	0.946
t-stat	*-4.41*	*13.3*	*20.7*	*24.9*	*28.7*	*41.1*
Conglos	-0.080	0.194	0.337	0.508	0.836	0.916
t-stat	*-3.92*	*13.8*	*21.0*	*25.7*	*30.6*	*43.5*
C-S	0.010	0.009	0.006	0.004	-0.020	-0.030
t-stat	*2.02*	*9.70*	*6.26*	*2.76*	*-4.21*	*-4.41*

Table 3. Firm Complexity and Anomalies in Cross-Sectional Regressions

The table presents Fama-MacBeth (1973) regressions of future returns on log of a complexity variable (indicated in the name of each column), log of an anomaly variable from Table 2 as indicated in the panels' headings, and their interaction. The regressions also include standard asset pricing controls (market beta, log of market cap, log of market-to-book, momentum, short-term reversal, investment-to-assets, profitability) and log of composite overpricing measure from Stambaugh et al. (2015), as well as its interaction with the anomaly variable. All independent variables, including complexity variables, are winsorized at 0.5% and 99.5%. Stocks priced below \$5 per share at the portfolio formation date are excluded from the sample. Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2018.

Panel A. Turnover Variability Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.148	0.150	0.149	0.161	0.173	0.173
t-stat	*1.16*	*1.17*	*1.16*	*1.24*	*1.16*	*1.15*
Log(Size)	-0.130	-0.129	-0.129	-0.129	-0.153	-0.155
t-stat	*-2.94*	*-2.91*	*-2.90*	*-2.89*	*-2.92*	*-2.95*
Log(MB)	-0.172	-0.173	-0.174	-0.175	-0.116	-0.114
t-stat	*-2.13*	*-2.13*	*-2.14*	*-2.13*	*-1.18*	*-1.16*
Mom	0.107	0.107	0.109	0.101	-0.144	-0.144
t-stat	*0.56*	*0.56*	*0.57*	*0.53*	*-0.63*	*-0.63*
Rev	0.001	0.001	0.001	0.001	0.004	0.004
t-stat	*0.22*	*0.20*	*0.22*	*0.25*	*0.92*	*0.92*
Inv	0.056	0.056	0.054	0.082	-0.022	-0.010
t-stat	*0.20*	*0.20*	*0.19*	*0.28*	*-0.06*	*-0.03*
GProf	0.047	0.047	0.047	0.053	0.018	0.018
t-stat	*0.86*	*0.85*	*0.86*	*0.96*	*0.28*	*0.27*
Over	-0.999	-1.004	-1.006	-1.044	-0.821	-0.817
t-stat	*-4.11*	*-4.11*	*-4.12*	*-4.30*	*-2.86*	*-2.85*
log(CVT)	2.684	2.658	2.665	2.533	4.347	4.404
t-stat	*2.10*	*2.07*	*2.07*	*1.99*	*3.19*	*3.21*
Over·CVT	-0.778	-0.770	-0.774	-0.741	-1.210	-1.224
t-stat	*-2.34*	*-2.31*	*-2.31*	*-2.24*	*-3.43*	*-3.45*
log(Comp)	0.115	0.131	0.314	0.041	0.058	0.068
t-stat	*1.12*	*1.33*	*1.18*	*0.94*	*1.49*	*1.63*
Comp·CVT	-0.307	-0.358	-0.978	-0.132	-0.168	-0.175
t-stat	*-2.30*	*-2.70*	*-2.57*	*-2.13*	*-2.75*	*-2.73*

Panel B. Analyst Disagreement Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.047	0.047	0.045	0.051	0.051	0.052
t-stat	*0.37*	*0.37*	*0.36*	*0.40*	*0.35*	*0.35*
Log(Size)	-0.040	-0.039	-0.040	-0.037	-0.036	-0.035
t-stat	*-1.26*	*-1.25*	*-1.25*	*-1.15*	*-1.01*	*-0.98*
Log(MB)	-0.157	-0.159	-0.158	-0.156	-0.091	-0.093
t-stat	*-1.90*	*-1.92*	*-1.91*	*-1.88*	*-0.91*	*-0.93*
Mom	0.185	0.182	0.184	0.191	-0.113	-0.115
t-stat	*0.98*	*0.97*	*0.98*	*1.01*	*-0.55*	*-0.56*
Rev	-0.002	-0.002	-0.002	-0.002	0.000	0.000
t-stat	*-0.50*	*-0.47*	*-0.48*	*-0.41*	*-0.02*	*-0.01*
Inv	-0.102	-0.107	-0.103	-0.099	-0.204	-0.196
t-stat	*-0.38*	*-0.40*	*-0.38*	*-0.36*	*-0.61*	*-0.59*
GProf	0.062	0.063	0.061	0.066	0.035	0.035
t-stat	*1.23*	*1.25*	*1.22*	*1.32*	*0.65*	*0.66*
Over	-1.154	-1.152	-1.136	-1.337	-1.159	-1.150
t-stat	*-3.32*	*-3.33*	*-3.26*	*-3.83*	*-2.94*	*-2.91*
log(Disp)	0.490	0.478	0.455	0.682	0.473	0.452
t-stat	*1.32*	*1.29*	*1.23*	*1.83*	*1.19*	*1.13*
Over·Disp	-0.129	-0.127	-0.121	-0.176	-0.116	-0.111
t-stat	*-1.34*	*-1.33*	*-1.25*	*-1.82*	*-1.12*	*-1.07*
log(Comp)	-0.181	-0.185	-0.494	-0.129	-0.157	-0.130
t-stat	*-1.37*	*-1.38*	*-1.30*	*-2.13*	*-2.43*	*-2.15*
Comp·Disp	-0.049	-0.042	-0.111	-0.037	-0.044	-0.033
t-stat	*-1.28*	*-1.10*	*-1.07*	*-2.32*	*-2.36*	*-1.94*

Panel C. Idiosyncratic Volatility Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.184	0.185	0.184	0.192	0.193	0.194
t-stat	*1.62*	*1.63*	*1.62*	*1.54*	*1.68*	*1.69*
Log(Size)	-0.132	-0.131	-0.131	-0.117	-0.134	-0.134
t-stat	*-3.69*	*-3.65*	*-3.64*	*-3.07*	*-3.71*	*-3.69*
Log(MB)	-0.130	-0.131	-0.132	-0.157	-0.130	-0.130
t-stat	*-1.66*	*-1.67*	*-1.68*	*-1.84*	*-1.63*	*-1.62*
Mom	0.089	0.089	0.089	-0.106	0.085	0.084
t-stat	*0.49*	*0.49*	*0.49*	*-0.56*	*0.48*	*0.47*
Rev	0.001	0.001	0.001	0.003	0.001	0.001
t-stat	*0.32*	*0.31*	*0.31*	*0.72*	*0.31*	*0.31*
Inv	0.054	0.049	0.052	0.071	0.066	0.070
t-stat	*0.20*	*0.18*	*0.19*	*0.23*	*0.24*	*0.25*
GProf	0.038	0.038	0.038	0.031	0.042	0.043
t-stat	*0.69*	*0.68*	*0.69*	*0.53*	*0.76*	*0.77*
Over	-4.879	-4.869	-4.853	-5.271	-4.798	-4.825
t-stat	*-6.04*	*-6.02*	*-5.99*	*-6.10*	*-5.93*	*-5.96*
log(IVol)	3.308	3.291	3.266	3.476	3.202	3.228
t-stat	*4.76*	*4.72*	*4.67*	*4.63*	*4.58*	*4.61*
Over·IVol	-0.898	-0.895	-0.890	-0.954	-0.873	-0.879
t-stat	*-4.57*	*-4.55*	*-4.51*	*-4.50*	*-4.43*	*-4.45*
log(Comp)	-0.649	-0.616	-1.880	-1.151	-0.301	-0.282
t-stat	*-2.32*	*-2.04*	*-2.25*	*-2.15*	*-2.54*	*-2.49*
Comp·IVol	-0.159	-0.146	-0.437	-0.245	-0.073	-0.068
t-stat	*-2.33*	*-2.04*	*-2.28*	*-2.27*	*-2.69*	*-2.66*

Panel D. Turnover Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.085	0.086	0.086	0.058	0.098	0.100
t-stat	*0.73*	*0.73*	*0.73*	*0.47*	*0.82*	*0.84*
Log(Size)	-0.013	-0.012	-0.012	0.014	-0.011	-0.012
t-stat	*-0.41*	*-0.36*	*-0.38*	*0.41*	*-0.34*	*-0.38*
Log(MB)	-0.147	-0.150	-0.148	-0.145	-0.153	-0.151
t-stat	*-1.91*	*-1.94*	*-1.92*	*-1.73*	*-1.98*	*-1.96*
Mom	0.247	0.246	0.248	0.133	0.243	0.241
t-stat	*1.47*	*1.47*	*1.48*	*0.75*	*1.45*	*1.43*
Rev	0.000	0.000	0.000	0.002	0.000	0.000
t-stat	*-0.05*	*-0.06*	*-0.04*	*0.43*	*-0.08*	*-0.08*
Inv	0.146	0.138	0.141	0.102	0.183	0.188
t-stat	*0.53*	*0.50*	*0.51*	*0.34*	*0.65*	*0.66*
GProf	0.076	0.075	0.075	0.060	0.077	0.076
t-stat	*1.38*	*1.37*	*1.37*	*1.07*	*1.41*	*1.41*
Over	-0.997	-0.998	-1.001	-1.103	-1.040	-1.038
t-stat	*-6.56*	*-6.56*	*-6.57*	*-6.50*	*-6.69*	*-6.71*
log(Turn)	0.135	0.132	0.133	0.105	0.129	0.133
t-stat	*1.98*	*1.95*	*1.94*	*1.64*	*1.80*	*1.84*
Over·Turn	-0.384	-0.376	-0.377	-0.335	-0.366	-0.375
t-stat	*-2.16*	*-2.13*	*-2.11*	*-1.99*	*-1.95*	*-1.99*
log(Comp)	-0.046	-0.073	-0.234	-0.064	-0.009	-0.007
t-stat	*-0.80*	*-1.26*	*-1.46*	*-1.16*	*-0.39*	*-0.32*
Comp·Turn	-0.091	-0.101	-0.292	-0.131	-0.069	-0.058
t-stat	*-1.06*	*-1.22*	*-1.24*	*-1.92*	*-2.02*	*-1.75*

Panel E. Investment Growth Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.036	-0.036	-0.036	-0.032	-0.031	-0.028
t-stat	*-0.25*	*-0.25*	*-0.25*	*-0.22*	*-0.21*	*-0.20*
Log(Size)	-0.031	-0.032	-0.030	-0.030	-0.031	-0.032
t-stat	*-0.84*	*-0.85*	*-0.80*	*-0.80*	*-0.84*	*-0.85*
Log(MB)	-0.200	-0.198	-0.202	-0.200	-0.196	-0.197
t-stat	*-2.42*	*-2.38*	*-2.44*	*-2.38*	*-2.35*	*-2.36*
Mom	0.401	0.404	0.401	0.407	0.412	0.411
t-stat	*2.42*	*2.44*	*2.42*	*2.45*	*2.49*	*2.48*
Rev	0.003	0.003	0.003	0.003	0.003	0.003
t-stat	*0.68*	*0.70*	*0.68*	*0.76*	*0.79*	*0.79*
Inv	-0.605	-0.608	-0.609	-0.654	-0.647	-0.643
t-stat	*-2.24*	*-2.25*	*-2.25*	*-2.38*	*-2.36*	*-2.35*
GProf	0.147	0.146	0.147	0.148	0.150	0.149
t-stat	*3.12*	*3.09*	*3.11*	*3.09*	*3.11*	*3.11*
IO	0.494	0.494	0.490	0.500	0.490	0.495
t-stat	*4.86*	*4.87*	*4.83*	*4.88*	*4.81*	*4.85*
IO·IG	0.022	0.024	0.023	0.021	0.047	0.050
t-stat	*0.43*	*0.45*	*0.44*	*0.40*	*0.87*	*0.92*
IG	0.006	0.005	0.009	0.013	0.000	-0.003
t-stat	*0.18*	*0.15*	*0.28*	*0.42*	*-0.01*	*-0.10*
log(Comp)	-0.070	-0.153	-0.072	-0.039	-0.031	-0.027
t-stat	*-1.27*	*-0.99*	*-1.24*	*-1.61*	*-1.31*	*-1.20*
Comp·IG	-0.078	-0.207	-0.110	-0.058	-0.046	-0.043
t-stat	*-2.22*	*-1.71*	*-2.76*	*-3.14*	*-2.71*	*-2.58*

Panel F. Asset Growth Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.029	-0.030	-0.030	-0.025	-0.024	-0.023
t-stat	*-0.21*	*-0.21*	*-0.21*	*-0.18*	*-0.17*	*-0.16*
Log(Size)	-0.033	-0.034	-0.031	-0.032	-0.033	-0.034
t-stat	*-0.88*	*-0.90*	*-0.84*	*-0.86*	*-0.88*	*-0.91*
Log(MB)	-0.184	-0.182	-0.186	-0.180	-0.177	-0.178
t-stat	*-2.27*	*-2.24*	*-2.30*	*-2.19*	*-2.17*	*-2.18*
Mom	0.401	0.403	0.402	0.406	0.409	0.409
t-stat	*2.44*	*2.46*	*2.44*	*2.46*	*2.49*	*2.49*
Rev	0.003	0.003	0.003	0.003	0.003	0.003
t-stat	*0.68*	*0.69*	*0.68*	*0.76*	*0.79*	*0.79*
Inv	-0.266	-0.287	-0.269	-0.283	-0.272	-0.271
t-stat	*-0.88*	*-0.95*	*-0.89*	*-0.93*	*-0.90*	*-0.89*
GProf	0.141	0.140	0.141	0.141	0.142	0.143
t-stat	*3.02*	*2.99*	*3.01*	*2.98*	*2.98*	*2.99*
IO	0.452	0.453	0.448	0.456	0.456	0.461
t-stat	*4.38*	*4.39*	*4.33*	*4.38*	*4.35*	*4.39*
IO·AG	0.324	0.327	0.322	0.348	0.371	0.371
t-stat	*1.68*	*1.69*	*1.67*	*1.77*	*1.85*	*1.84*
AG	-0.273	-0.284	-0.268	-0.282	-0.292	-0.289
t-stat	*-2.87*	*-3.02*	*-2.82*	*-2.92*	*-3.02*	*-3.00*
log(Comp)	-0.043	-0.107	-0.045	-0.023	-0.017	-0.013
t-stat	*-0.78*	*-0.67*	*-0.77*	*-0.94*	*-0.69*	*-0.58*
Comp·AG	-0.249	-0.591	-0.295	-0.165	-0.150	-0.139
t-stat	*-2.31*	*-1.71*	*-2.51*	*-2.89*	*-2.99*	*-2.86*

Panel G. Cumulative Issuance Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.012	0.011	0.012	0.024	0.028	0.031
t-stat	*0.08*	*0.08*	*0.08*	*0.16*	*0.19*	*0.21*
Log(Size)	-0.043	-0.044	-0.041	-0.043	-0.044	-0.045
t-stat	*-1.26*	*-1.28*	*-1.19*	*-1.24*	*-1.27*	*-1.30*
Log(MB)	-0.148	-0.146	-0.152	-0.144	-0.143	-0.143
t-stat	*-1.80*	*-1.76*	*-1.85*	*-1.74*	*-1.72*	*-1.72*
Mom	0.337	0.340	0.337	0.352	0.355	0.355
t-stat	*2.16*	*2.18*	*2.16*	*2.26*	*2.29*	*2.29*
Rev	0.001	0.001	0.001	0.001	0.001	0.001
t-stat	*0.22*	*0.21*	*0.21*	*0.34*	*0.34*	*0.34*
Inv	-0.133	-0.138	-0.139	-0.194	-0.176	-0.180
t-stat	*-0.44*	*-0.46*	*-0.46*	*-0.63*	*-0.57*	*-0.58*
GProf	0.143	0.141	0.142	0.146	0.146	0.146
t-stat	*3.18*	*3.14*	*3.16*	*3.27*	*3.22*	*3.23*
IO	0.371	0.369	0.363	0.384	0.389	0.396
t-stat	*4.30*	*4.27*	*4.22*	*4.47*	*4.52*	*4.59*
IO*CI	0.782	0.776	0.773	0.764	0.756	0.759
t-stat	*3.99*	*3.98*	*3.94*	*3.80*	*3.82*	*3.85*
CI	-0.683	-0.690	-0.687	-0.675	-0.678	-0.685
t-stat	*-5.37*	*-5.50*	*-5.39*	*-5.31*	*-5.51*	*-5.53*
log(Comp)	-0.105	-0.289	-0.121	-0.052	-0.044	-0.039
t-stat	*-1.89*	*-1.90*	*-2.08*	*-2.21*	*-1.90*	*-1.76*
Comp*CI	-0.217	-0.552	-0.229	-0.139	-0.112	-0.090
t-stat	*-1.92*	*-1.73*	*-2.01*	*-2.80*	*-2.36*	*-2.05*

Panel H. Retained Earnings Effect

Comp=	Cong	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.067	-0.067	-0.067	-0.060	-0.061	-0.059
t-stat	*-0.49*	*-0.49*	*-0.49*	*-0.44*	*-0.45*	*-0.43*
Log(Size)	-0.021	-0.022	-0.019	-0.020	-0.021	-0.022
t-stat	*-0.64*	*-0.66*	*-0.57*	*-0.63*	*-0.65*	*-0.66*
Log(MB)	-0.108	-0.107	-0.110	-0.108	-0.104	-0.104
t-stat	*-1.37*	*-1.36*	*-1.40*	*-1.35*	*-1.31*	*-1.31*
Mom	0.401	0.404	0.400	0.410	0.412	0.411
t-stat	*2.47*	*2.50*	*2.47*	*2.51*	*2.54*	*2.53*
Rev	0.002	0.002	0.002	0.002	0.002	0.002
t-stat	*0.43*	*0.43*	*0.43*	*0.49*	*0.53*	*0.53*
Inv	-0.602	-0.605	-0.607	-0.632	-0.624	-0.625
t-stat	*-2.43*	*-2.44*	*-2.44*	*-2.52*	*-2.50*	*-2.50*
GProf	0.138	0.138	0.138	0.140	0.141	0.142
t-stat	*3.09*	*3.08*	*3.07*	*3.12*	*3.10*	*3.13*
IO	0.583	0.573	0.574	0.593	0.605	0.603
t-stat	*4.87*	*4.75*	*4.79*	*4.96*	*5.04*	*5.02*
IO*RE	-0.519	-0.487	-0.509	-0.506	-0.524	-0.512
t-stat	*-3.31*	*-3.03*	*-3.22*	*-3.16*	*-3.20*	*-3.14*
RE	0.256	0.258	0.259	0.246	0.252	0.245
t-stat	*2.02*	*2.07*	*2.04*	*1.93*	*1.97*	*1.92*
log(Comp)	-0.139	-0.331	-0.154	-0.082	-0.068	-0.069
t-stat	*-2.14*	*-1.83*	*-2.19*	*-2.71*	*-2.41*	*-2.51*
Comp*RE	0.222	0.476	0.224	0.148	0.116	0.130
t-stat	*2.50*	*1.94*	*2.43*	*3.49*	*2.98*	*3.41*

Table 4. Anomalies for Low-Complexity Conglomerates and High-Complexity Conglomerates

The table presents five-factor Fama and French (2015) alphas across five-by-three independent sorts on complexity and the variables indicated in the panels' headings. Complexity is measured as within-firm coefficient of variation (standard deviation divided by average) of segment-level imputed market-to-book ratios (RSZ measure). The sorts on complexity split firms into zero-complexity (single-segment) firms (Zero row), conglomerates with below-median complexity (Low row) and conglomerates with above-median complexity (High row). Stocks priced below $5 per share at the portfolio formation date are excluded from the sample. Detailed definitions of sorting variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2018.

Panel A. Turnover Variability Sorts

	Low	**CVT2**	**CVT3**	**CVT4**	**High**	**L-H**
Zero	0.055	0.210	0.216	0.066	-0.006	0.061
t-stat	*0.65*	*2.07*	*2.08*	*0.43*	*-0.05*	*0.39*
Low	0.037	-0.402	-0.244	0.054	-0.179	0.216
t-stat	*0.40*	*-2.41*	*-1.60*	*0.29*	*-0.96*	*1.09*
High	-0.021	-0.141	-0.175	-0.451	-0.934	0.913
t-stat	*-0.22*	*-1.14*	*-1.29*	*-2.45*	*-2.67*	*2.40*
H-Z	-0.076	-0.351	-0.391	-0.517	-0.927	0.851
t-stat	*-0.54*	*-2.18*	*-2.25*	*-2.12*	*-2.67*	*2.13*
H-L	-0.058	0.261	0.069	-0.505	-0.755	0.697
t-stat	*-0.42*	*1.26*	*0.34*	*-1.95*	*-2.38*	*1.91*

Panel B. Analyst Disagreement Sorts

	Low	**Disp2**	**disp3**	**disp4**	**High**	**L-H**
Zero	0.266	0.056	0.152	0.208	0.012	0.254
t-stat	*3.68*	*0.51*	*1.64*	*1.56*	*0.08*	*1.72*
Low	0.009	-0.116	0.018	0.130	-0.144	0.176
t-stat	*0.05*	*-0.85*	*0.12*	*0.71*	*-0.64*	*0.60*
High	0.050	-0.096	-0.364	-0.054	-0.708	0.796
t-stat	*0.52*	*-0.60*	*-2.98*	*-0.33*	*-3.98*	*3.71*
H-Z	-0.222	-0.152	-0.516	-0.262	-0.720	0.525
t-stat	*-2.24*	*-0.79*	*-3.24*	*-1.27*	*-3.46*	*2.33*
H-L	0.041	0.020	-0.382	-0.184	-0.564	0.620
t-stat	*0.18*	*0.11*	*-2.05*	*-0.78*	*-2.41*	*1.99*

Panel C. Idiosyncratic Volatility Sorts

	Low	IVol2	IVol3	IVol4	High	L-H
Zero	0.070	0.157	-0.101	0.142	-0.163	0.233
t-stat	*0.73*	*1.60*	*-0.88*	*1.40*	*-1.23*	*1.24*
Low	0.100	-0.167	-0.185	-0.008	-0.576	0.675
t-stat	*1.05*	*-1.52*	*-1.65*	*-0.05*	*-2.33*	*2.35*
High	-0.028	-0.221	-0.237	-0.166	-0.912	0.884
t-stat	*-0.36*	*-2.08*	*-1.95*	*-1.08*	*-4.68*	*3.91*
H-Z	-0.097	-0.378	-0.136	-0.307	-0.749	0.652
t-stat	*-0.85*	*-2.66*	*-0.86*	*-1.70*	*-3.98*	*2.85*
H-L	-0.127	-0.054	-0.052	-0.158	-0.336	0.209
t-stat	*-1.10*	*-0.49*	*-0.32*	*-0.88*	*-1.40*	*0.76*

Panel D. Turnover Sorts

	Low	Turn2	Turn3	Turn4	High	L-H
Zero	-0.004	-0.009	0.117	0.224	0.170	-0.174
t-stat	*-0.05*	*-0.10*	*1.25*	*2.86*	*1.51*	*-1.21*
Low	0.029	-0.158	-0.104	-0.094	-0.221	0.250
t-stat	*0.22*	*-1.81*	*-0.90*	*-0.88*	*-1.33*	*1.18*
High	0.038	-0.185	-0.335	-0.124	-0.446	0.485
t-stat	*0.35*	*-1.90*	*-3.11*	*-1.04*	*-2.47*	*2.19*
H-Z	0.043	-0.176	-0.451	-0.348	-0.616	0.659
t-stat	*0.28*	*-1.35*	*-3.29*	*-2.35*	*-3.12*	*2.71*
H-L	0.009	-0.028	-0.231	-0.030	-0.225	0.234
t-stat	*0.06*	*-0.19*	*-1.59*	*-0.21*	*-1.26*	*0.95*

Panel E. Investment Growth Sorts

	Low	IG2	IG3	IG4	High	L-H
Zero	0.267	0.263	0.261	0.144	0.131	0.136
t-stat	*2.65*	*2.90*	*2.94*	*1.52*	*1.34*	*1.14*
Low	0.088	0.243	-0.142	-0.113	-0.368	0.456
t-stat	*0.69*	*2.12*	*-1.35*	*-0.94*	*-2.39*	*2.12*
High	0.044	-0.191	-0.183	-0.043	-0.343	0.388
t-stat	*0.31*	*-1.40*	*-2.01*	*-0.32*	*-2.24*	*1.75*
H-Z	-0.223	-0.454	-0.444	-0.187	-0.474	0.251
t-stat	*-1.17*	*-2.92*	*-3.22*	*-1.06*	*-2.79*	*0.96*
H-L	-0.044	-0.434	-0.041	0.069	0.025	-0.068
t-stat	*-0.22*	*-2.58*	*-0.34*	*0.42*	*0.13*	*-0.23*

Panel F. Asset Growth Sorts

	Low	AG2	AG3	AG4	High	L-H
Zero	0.135	0.158	0.048	0.255	0.231	-0.096
t-stat	*1.33*	*1.70*	*0.48*	*2.50*	*2.51*	*-0.76*
Low	-0.049	-0.169	-0.104	-0.096	0.068	-0.118
t-stat	*-0.40*	*-1.27*	*-0.90*	*-0.67*	*0.58*	*-0.65*
High	-0.156	-0.009	-0.111	-0.275	-0.595	0.439
t-stat	*-1.30*	*-0.06*	*-1.15*	*-2.43*	*-3.72*	*2.70*
H-Z	-0.291	-0.167	-0.158	-0.530	-0.826	0.535
t-stat	*-1.81*	*-0.86*	*-1.19*	*-3.11*	*-4.39*	*2.42*
H-L	-0.106	0.160	-0.007	-0.180	-0.663	0.557
t-stat	*-0.68*	*0.90*	*-0.05*	*-1.09*	*-3.68*	*2.54*

Panel G. Cumulative Issuance Sorts

	Low	CI2	CI3	CI4	High	L-H
Zero	0.103	-0.128	0.195	0.274	0.069	0.034
t-stat	*1.14*	*-1.39*	*2.19*	*2.48*	*0.84*	*0.27*
Low	-0.032	-0.020	-0.238	-0.080	-0.283	0.251
t-stat	*-0.37*	*-0.21*	*-1.14*	*-0.58*	*-1.85*	*1.40*
High	0.267	-0.119	-0.136	-0.452	-0.545	0.811
t-stat	*1.99*	*-1.18*	*-0.93*	*-2.92*	*-3.55*	*4.38*
H-Z	0.164	0.003	-0.331	-0.731	-0.614	0.778
t-stat	*1.07*	*0.02*	*-1.78*	*-3.60*	*-3.31*	*3.50*
H-L	0.298	-0.069	0.102	-0.324	-0.262	0.560
t-stat	*2.04*	*-0.50*	*0.34*	*-1.72*	*-1.41*	*2.20*

Panel H. Retained Earnings Sorts

	Low	RE2	RE3	RE4	High	H-L
Zero	0.264	0.193	0.098	0.013	0.113	-0.151
t-stat	*2.46*	*2.26*	*1.12*	*0.14*	*0.98*	*-0.96*
Low	-0.223	-0.232	0.037	0.059	-0.012	0.211
t-stat	*-1.24*	*-1.73*	*0.45*	*0.58*	*-0.10*	*1.09*
High	-0.782	-0.327	-0.007	-0.089	-0.166	0.616
t-stat	*-4.27*	*-2.45*	*-0.07*	*-0.91*	*-1.26*	*2.97*
H-Z	-1.047	-0.520	-0.105	-0.102	-0.279	0.767
t-stat	*-5.16*	*-2.93*	*-0.75*	*-0.78*	*-1.86*	*3.02*
H-L	-0.560	-0.094	-0.043	-0.148	-0.154	0.405
t-stat	*-2.62*	*-0.54*	*-0.38*	*-1.18*	*-1.13*	*1.52*

Table 5. Firm Complexity and Anomalies: Conglomerates Only

The table repeats Fama-MacBeth regressions from Table 3 using conglomerates-only subsample. Conglomerates are defined as firms with business segments in more than one industry, industries are defined using two-digit SIC codes. The regressions run future returns on a complexity measure (as indicated by the name of each column), an anomaly variable (indicated in the title of each panel), the interaction of complexity and the anomaly variable, and controls described in the heading of Table 3. Stocks priced below \$5 per share at the portfolio formation date are excluded from the sample. All independent variables, including complexity variables, are winsorized at 0.5% and 99.5%. Detailed definitions of sorting variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1978 to December 2018.

Panel A. Turnover Variability Effect

Comp=	**NSeg**	**1-HHI**	**RSZ**	CV_{OL}	CV_{SGA}
Beta	0.048	0.002	0.095	0.036	0.159
t-stat	*0.37*	*0.01*	*0.71*	*0.27*	*1.02*
Log(Size)	-0.106	-0.032	-0.106	-0.078	-0.114
t-stat	*-2.64*	*-1.12*	*-2.62*	*-2.13*	*-2.49*
Log(MB)	-0.270	-0.261	-0.311	-0.228	-0.286
t-stat	*-3.37*	*-3.15*	*-3.50*	*-2.76*	*-2.84*
Mom	0.085	0.088	0.017	0.228	-0.221
t-stat	*0.38*	*0.41*	*0.07*	*0.95*	*-0.73*
Rev	0.002	-0.003	0.003	0.003	0.008
t-stat	*0.40*	*-0.50*	*0.59*	*0.66*	*1.38*
Inv	0.131	0.384	0.171	0.081	0.226
t-stat	*0.41*	*1.12*	*0.54*	*0.20*	*0.55*
GProf	0.086	0.144	0.099	0.121	0.116
t-stat	*1.63*	*2.20*	*1.83*	*1.83*	*1.93*
Over	-1.027	-1.397	-1.036	-0.649	-0.950
t-stat	*-3.41*	*-5.06*	*-3.36*	*-2.14*	*-2.57*
log(CVT)	2.245	1.620	2.257	1.724	3.840
t-stat	*1.27*	*0.93*	*1.20*	*1.49*	*1.68*
Over·CVT	-0.544	-0.649	-0.719	-0.520	-1.086
t-stat	*-1.19*	*-2.35*	*-1.48*	*-1.00*	*-1.83*
log(Comp)	0.103	-0.896	0.001	0.094	0.011
t-stat	*1.87*	*-2.42*	*0.12*	*2.02*	*2.18*
Comp·CVT	-0.274	-0.789	-0.002	-0.134	-0.020
t-stat	*-2.40*	*-1.72*	*-0.16*	*-1.69*	*-1.85*

Panel B. Analyst Disagreement Effect

Comp=	**NSeg**	**1-HHI**	**RSZ**	CV_{OL}	CV_{SGA}
Beta	0.105	0.116	0.153	0.174	0.168
t-stat	*0.72*	*0.79*	*1.01*	*0.97*	*1.11*
Log(Size)	-0.080	-0.085	-0.065	-0.073	-0.067
t-stat	*-2.31*	*-2.42*	*-1.71*	*-1.73*	*-1.78*
Log(MB)	-0.319	-0.310	-0.363	-0.294	-0.356
t-stat	*-3.19*	*-3.10*	*-3.37*	*-2.22*	*-3.32*
Mom	-0.094	-0.088	-0.199	-0.492	-0.144
t-stat	*-0.37*	*-0.35*	*-0.74*	*-1.56*	*-0.55*
Rev	-0.002	-0.002	-0.002	0.006	-0.002
t-stat	*-0.27*	*-0.32*	*-0.32*	*0.78*	*-0.26*
Inv	0.165	0.210	0.257	0.048	0.296
t-stat	*0.40*	*0.51*	*0.61*	*0.10*	*0.70*
GProf	0.129	0.125	0.153	0.165	0.136
t-stat	*1.65*	*1.62*	*1.74*	*1.69*	*1.57*
Over	-1.054	-1.027	-1.331	-1.234	-1.330
t-stat	*-2.03*	*-1.95*	*-2.47*	*-1.83*	*-2.53*
log(Disp)	0.378	0.338	0.667	0.471	0.631
t-stat	*0.66*	*0.59*	*1.16*	*0.67*	*1.10*
Over·Disp	-0.105	-0.097	-0.152	-0.091	-0.153
t-stat	*-0.72*	*-0.65*	*-1.01*	*-0.49*	*-1.03*
log(Comp)	-0.228	-0.426	-0.307	-0.335	-0.173
t-stat	*-0.65*	*-0.66*	*-2.35*	*-2.26*	*-1.50*
Comp·Disp	-0.029	-0.065	-0.078	-0.088	-0.053
t-stat	*-0.30*	*-0.33*	*-2.06*	*-2.18*	*-1.56*

Panel C. Idiosyncratic Volatility Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.103	0.113	0.155	0.233	0.227
t-stat	*0.81*	*0.88*	*1.19*	*1.49*	*1.44*
Log(Size)	-0.067	-0.075	-0.068	-0.066	-0.064
t-stat	*-1.95*	*-2.20*	*-1.95*	*-1.62*	*-1.55*
Log(MB)	-0.257	-0.254	-0.301	-0.334	-0.331
t-stat	*-3.05*	*-2.97*	*-3.35*	*-3.03*	*-3.03*
Mom	0.069	0.053	0.017	-0.269	-0.270
t-stat	*0.31*	*0.23*	*0.07*	*-0.88*	*-0.88*
Rev	0.002	0.003	0.004	0.009	0.009
t-stat	*0.45*	*0.59*	*0.73*	*1.46*	*1.48*
Inv	0.346	0.376	0.379	0.545	0.563
t-stat	*0.94*	*1.00*	*0.96*	*1.14*	*1.19*
GProf	0.099	0.093	0.141	0.176	0.174
t-stat	*1.58*	*1.47*	*2.18*	*2.27*	*2.22*
Over	0.090	0.054	-0.006	0.156	0.053
t-stat	*0.31*	*0.18*	*-0.02*	*0.44*	*0.14*
log(IVol)	3.633	3.751	3.333	3.614	3.455
t-stat	*3.82*	*4.05*	*3.44*	*3.12*	*3.04*
Over·IVol	-1.050	-1.056	-0.979	-1.017	-1.038
t-stat	*-4.25*	*-4.33*	*-3.81*	*-3.36*	*-3.48*
log(Comp)	-0.225	-0.336	0.015	0.066	-0.045
t-stat	*-1.08*	*-0.88*	*0.21*	*0.92*	*-0.56*
Comp·IVol	1.027	-9.718	-2.890	-2.144	3.357
t-stat	*0.09*	*-0.48*	*-0.77*	*-0.59*	*0.86*

Panel D. Turnover Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	0.051	0.055	0.164	0.112	0.108
t-stat	*0.43*	*0.47*	*1.17*	*0.96*	*0.92*
Log(Size)	0.001	-0.005	-0.002	0.002	-0.001
t-stat	*0.02*	*-0.15*	*-0.06*	*0.07*	*-0.02*
Log(MB)	-0.303	-0.293	-0.299	-0.332	-0.329
t-stat	*-3.97*	*-3.85*	*-3.42*	*-4.33*	*-4.32*
Mom	0.121	0.129	-0.156	0.050	0.057
t-stat	*0.58*	*0.63*	*-0.59*	*0.23*	*0.26*
Rev	-0.001	-0.001	0.002	-0.001	-0.001
t-stat	*-0.24*	*-0.23*	*0.37*	*-0.28*	*-0.20*
Inv	0.126	0.142	0.215	0.177	0.193
t-stat	*0.46*	*0.51*	*0.62*	*0.62*	*0.69*
GProf	0.142	0.140	0.144	0.134	0.129
t-stat	*2.57*	*2.51*	*2.39*	*2.48*	*2.41*
Over	-0.651	-0.629	-0.820	-0.797	-0.795
t-stat	*-3.26*	*-3.13*	*-3.01*	*-3.71*	*-3.68*
log(Turn)	0.230	0.265	0.210	0.242	0.262
t-stat	*2.31*	*2.69*	*2.14*	*2.40*	*2.56*
Over·Turn	-0.594	-0.661	-0.465	-0.576	-0.609
t-stat	*-2.52*	*-2.73*	*-1.91*	*-2.38*	*-2.47*
log(Comp)	-0.229	-0.143	0.128	0.058	0.065
t-stat	*-1.51*	*-0.53*	*2.23*	*1.29*	*1.32*
Comp·Turn	-0.134	-0.703	-0.226	-0.160	-0.172
t-stat	*-0.69*	*-1.75*	*-3.41*	*-2.59*	*-2.73*

Panel E. Investment Growth Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.143	-0.139	-0.108	-0.115	-0.094
t-stat	*-1.04*	*-1.01*	*-0.76*	*-0.83*	*-0.66*
Log(Size)	-0.008	-0.012	-0.009	-0.012	-0.009
t-stat	*-0.25*	*-0.36*	*-0.28*	*-0.38*	*-0.29*
Log(MB)	-0.259	-0.245	-0.299	-0.286	-0.290
t-stat	*-3.15*	*-3.00*	*-3.56*	*-3.39*	*-3.43*
Mom	0.230	0.236	0.253	0.221	0.255
t-stat	*1.05*	*1.08*	*1.08*	*0.96*	*1.11*
Rev	-0.004	-0.004	-0.003	-0.003	-0.003
t-stat	*-0.73*	*-0.79*	*-0.57*	*-0.49*	*-0.54*
Inv	-0.727	-0.770	-1.052	-0.801	-0.983
t-stat	*-2.44*	*-2.51*	*-3.15*	*-2.51*	*-2.96*
GProf	0.174	0.170	0.203	0.197	0.205
t-stat	*3.11*	*3.02*	*3.57*	*3.59*	*3.47*
IO	0.420	0.436	0.456	0.463	0.441
t-stat	*4.01*	*4.10*	*4.14*	*4.18*	*3.98*
IO·IG	0.031	0.099	0.169	0.129	0.243
t-stat	*0.24*	*0.81*	*1.16*	*1.01*	*1.60*
IG	0.276	-0.126	0.048	0.126	-0.005
t-stat	*1.62*	*-1.25*	*0.35*	*0.99*	*-0.04*
log(Comp)	-0.093	-0.107	-0.026	0.032	0.015
t-stat	*-1.08*	*-0.61*	*-0.83*	*1.22*	*0.52*
Comp·IG	-0.388	0.151	-0.101	-0.096	-0.072
t-stat	*-2.65*	*0.67*	*-2.20*	*-2.38*	*-1.50*

Panel F. Asset Growth Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.100	-0.073	0.003	-0.083	-0.084
t-stat	*-0.72*	*-0.51*	*0.02*	*-0.59*	*-0.62*
Log(Size)	-0.018	-0.019	-0.030	-0.017	-0.020
t-stat	*-0.53*	*-0.56*	*-0.80*	*-0.50*	*-0.58*
Log(MB)	-0.239	-0.258	-0.183	-0.261	-0.266
t-stat	*-3.13*	*-3.15*	*-1.90*	*-3.24*	*-3.30*
Mom	0.186	0.148	0.095	0.156	0.164
t-stat	*0.98*	*0.74*	*0.41*	*0.79*	*0.83*
Rev	0.002	0.001	0.003	0.001	0.002
t-stat	*0.36*	*0.19*	*0.45*	*0.23*	*0.41*
Inv	-0.158	-0.399	-0.530	-0.271	-0.301
t-stat	*-0.46*	*-1.07*	*-1.24*	*-0.73*	*-0.77*
GProf	0.047	0.087	0.038	0.090	0.078
t-stat	*1.78*	*2.10*	*0.83*	*2.13*	*1.96*
IO	0.432	0.482	0.440	0.487	0.477
t-stat	*3.61*	*4.07*	*3.28*	*4.14*	*4.09*
IO·AG	0.201	0.041	-0.118	0.113	0.210
t-stat	*0.53*	*0.10*	*-0.25*	*0.25*	*0.48*
AG	-0.113	0.263	0.683	0.145	0.352
t-stat	*-0.26*	*0.71*	*1.65*	*0.39*	*0.97*
log(Comp)	-0.080	-0.014	0.040	-0.010	0.014
t-stat	*-0.96*	*-0.48*	*1.17*	*-0.33*	*0.51*
Comp·AG	-0.106	-0.197	-0.293	-0.143	-0.205
t-stat	*-0.31*	*-1.80*	*-2.30*	*-1.40*	*-2.33*

Panel G. Cumulative Issuance Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.028	-0.071	-0.026	0.023	-0.024
t-stat	*-0.20*	*-0.51*	*-0.19*	*0.14*	*-0.17*
Log(Size)	-0.058	-0.045	-0.055	-0.062	-0.051
t-stat	*-1.71*	*-1.31*	*-1.61*	*-1.68*	*-1.55*
Log(MB)	-0.233	-0.235	-0.245	-0.174	-0.217
t-stat	*-2.79*	*-2.88*	*-2.92*	*-1.90*	*-2.80*
Mom	0.184	0.186	0.183	0.052	0.103
t-stat	*0.84*	*0.86*	*0.83*	*0.22*	*0.53*
Rev	-0.002	-0.004	-0.003	-0.001	-0.002
t-stat	*-0.47*	*-0.80*	*-0.53*	*-0.15*	*-0.39*
Inv	-0.080	-0.088	-0.252	-0.138	-0.077
t-stat	*-0.25*	*-0.28*	*-0.77*	*-0.45*	*-0.29*
GProf	0.171	0.168	0.184	0.087	0.104
t-stat	*3.19*	*3.13*	*3.36*	*1.73*	*2.19*
IO	0.468	0.405	0.502	0.493	0.545
t-stat	*4.35*	*3.94*	*4.68*	*4.07*	*5.13*
IO·CI	0.320	0.371	0.342	0.180	0.252
t-stat	*1.23*	*1.36*	*1.15*	*0.63*	*0.98*
CI	-0.516	-0.442	-0.468	-0.355	-0.539
t-stat	*-2.48*	*-1.49*	*-2.01*	*-1.60*	*-2.84*
log(Comp)	-0.006	-0.056	-0.006	-0.002	0.000
t-stat	*-2.45*	*-2.17*	*-2.07*	*-1.03*	*-0.16*
Comp·CI	-0.022	-0.101	-0.031	-0.014	-0.013
t-stat	*-2.61*	*-1.14*	*-2.72*	*-1.91*	*-1.81*

Panel H. Retained Earnings Effect

Comp=	NSeg	1-HHI	RSZ	CV_{OL}	CV_{SGA}
Beta	-0.084	-0.065	-0.044	-0.098	-0.089
t-stat	*-0.63*	*-0.48*	*-0.32*	*-0.71*	*-0.63*
Log(Size)	-0.011	-0.016	-0.019	-0.016	-0.016
t-stat	*-0.33*	*-0.48*	*-0.55*	*-0.49*	*-0.48*
Log(MB)	-0.265	-0.275	-0.253	-0.232	-0.219
t-stat	*-3.01*	*-2.99*	*-2.74*	*-2.68*	*-2.50*
Mom	0.217	0.218	0.188	0.167	0.158
t-stat	*0.95*	*0.94*	*0.81*	*0.84*	*0.79*
Rev	0.000	0.001	0.000	0.002	0.002
t-stat	*0.07*	*0.19*	*0.02*	*0.43*	*0.42*
Inv	-0.740	-0.766	-0.941	-0.729	-0.809
t-stat	*-2.45*	*-2.35*	*-2.94*	*-2.97*	*-3.40*
GProf	0.222	0.235	0.230	0.085	0.095
t-stat	*4.22*	*4.50*	*4.12*	*1.99*	*2.12*
IO	0.450	0.479	0.455	0.553	0.523
t-stat	*3.15*	*3.10*	*2.87*	*3.48*	*3.14*
IO·RE	0.034	0.127	0.228	0.047	0.166
t-stat	*0.16*	*0.56*	*0.91*	*0.18*	*0.59*
RE	0.203	0.032	-0.080	0.024	-0.044
t-stat	*0.77*	*0.20*	*-0.44*	*0.14*	*-0.23*
log(Comp)	-0.037	-0.006	-0.011	-0.004	-0.005
t-stat	*-0.91*	*-1.54*	*-2.69*	*-1.57*	*-1.67*
Comp·RE	-0.022	0.009	0.024	0.008	0.012
t-stat	*-0.29*	*1.27*	*2.44*	*1.50*	*1.99*