Supplementary Tests for

Firm Complexity and

Conglomerates Expected Returns

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Abstract

The document collects supplementary tests for the paper "Firm Complexity and Conglomerates Expected Returns". Section 1 and 3 present robustness results from replacing the Comp=1-HHI measure of complexity by either number of segments (NSeg) or the RSZ measure (variability of segment-level market-to-book within the conglomerate). Section 2 controls for other anomalies often linked to overpricing of high-disagreement, short-sale constrained stocks. Section 4 explores the potential link between the complexity effect and coinsurance. Section 5 considers the relation between the complexity effect and the diversification discount of Berger and Ofek (1995), and Section 6 looks at whether financial constraints factors can explain the complexity effect.

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1 Alternative Measures of Complexity

Table 1A establishes robustness of the complexity effect in portfolio sorts by repeating Panel A of Table 3 in the paper with the Comp=1-HHI measure replaced by NSeg (the number of segments with different two-digit SIC codes) and the RSZ measure (the variability of segment-level market-to-book).

Table 3 in the paper estimates the difference in five-factor Fama and French (2015) alphas (henceforth FF5 alphas) between single-segment firms and high/low-complexity conglomerates at 35/20 bp per month (both highly significant) and the difference in FF5 alpha between low- and high-complexity conglomerates at 15 bp per month (significant at the 10% level). Panel A1 of Table 1A uses NSeg instead of Comp, but its estimates of these three alpha differentials fall within 3 bp of what Table 3 in the paper reports. Panel B1 of Table 1A uses the RSZ measure and comes up with larger estimates: the difference in FF5 alphas between single-segment firms and high/low-complexity conglomerates is 49/28 bp per month, and the similar difference between low- and high-complexity conglomerates is 21 bp per month.

Panels A1 and B1 of Table 1A also agree with Table 3 in the paper that controlling for momentum does not affect the three alpha differentials above and controlling for RMW is important in discovering them, since conglomerates tend to be abnormally profitable value firms that have returns similar to returns of other value firms and not commensurate with their profitability. The latter result is confirmed in Panels A2 and B2 that estimate the RMW beta differential between conglomerates and single-segment firms to be between 0.42 and 0.58, similar to Panel A2 of Table 3 in the paper (where this differential is 0.43-0.48).

Panels A1 and B1 of Table 1A similarly confirm the result in Panel A1 of Table 3 in the paper that the complexity effect does not significantly decline in the second part of the sample (1999-2016, after SFAS 131 was enacted).

Table 2A redoes the regressions in the three rightmost columns in Table 4 in the paper replacing Comp with NSeg (Panel A of Table 2A) or the RSZ measure (Panel B). The regressions aim at verifying that the degree of complexity matters: the left column in both panels regresses future returns on standard asset-pricing controls and high and low complexity dummies (HiSeg/LoSeg and HiRSZ/LoRSZ). HiSeg is 1 for conglomerates with more than two segments with different two-digit SIC codes and 0 otherwise, LoSeg is 1 only for conglomerates with two segments and 0 for all other firms (both HiSeg and LoSeg are 0 for single-segment firms). Likewise, to form HiRSZ/LoRSZ, I sort all conglomerates on the RSZ measure - those with RSZ above median have HiRSZ of 1 and LoRSZ of 0 and vice versa, and all single-segment firms have both HiRSZ and LoRSZ equal to 0. The left column of Panel A has HiSeg significant and LoSeg marginally significant, the left column of Panel B has HiRSZ significant and LoSeg insignificant (like column nine of Table 4 in the paper). In both cases, the negative slope on HiSeg/HiRSZ materially exceeds the slope on LoSeg/LoRSZ, which implies that expected returns of high-complexity conglomerates are lower than expected returns of low-complexity conglomerates.

The middle column in Panels A and B of Table 2A repeats column 10 of Table 4 in the paper using HiSeg or HiRSZ, respectively, along with the Conglo dummy. The slope on HiSeg/HiRSZ is now the incremental effect of high complexity on returns. In contrast to column 10 of Table 4 in the paper, where both Conglo and HiComp narrowly missed significance at 10% level, the middle column in Panel A of Table 2A reports that Conglo is significant and HiSeg is not, while the middle column of Panel B finds that HiRSZ is significant and Conglo is not. Since Table 4 in the paper shows that Comp, NSeg, and

RSZ are all significant, the cases of insignificance in Table 2A re likely to be a power issue, and overall Table 2A corroborates suggestive evidence in columns 9 and 10 of Table 4 in the paper and concludes that low-complexity conglomerates have lower expected returns than single-segment firms, and expected returns to high-complexity conglomerates are even lower.

Lastly, the rightmost columns in Panels A and B of Table 2A repeat column 11 of Table 4 in the paper, restricting the sample to conglomerates only, but using HiSeg or HiRSZ instead of HiComp. HiSeg comes out insignificant, while HiRSZ is significant at the 10% level, just like HiComp in column 11 of Table 4. Looking across complexity measures, it seems that Comp and RSZ support each other in the message ”the degree of complexity matters”, while NSeg faces more power issues, probably because number of segments is a crude measure of complexity, and a look into their relative importance and the difference between their industries is needed to truly measure complexity of a conglomerate.

2 Complexity Effect and (Seemingly) Related Anomalies

The main hypothesis of my paper is that the complexity effect arises because there is relatively more disagreement about conglomerates, and the interaction between investor disagreement and short-sale constraints creates overpricing, as Miller (1977) suggested. Table 2 in the paper presents the evidence that conglomerates indeed have higher analyst disagreement, larger analyst forecast errors, lower institutional ownership and lower analyst following than comparable firms, and more complex conglomerates have even higher analyst disagreement and forecast errors, and even lower institutional ownership and analyst following.

Several other anomalies, such as the idiosyncratic volatility effect of Ang, Hodrick, Xing, and Zhang (2006) and the analyst disagreement effect of Diether, Malloy, and Scherbina (2002), are often tracked back to the Miller (1977) explanation, which would imply a negative relation between expected returns and any measure of disagreement or short-sale constraints.

A priori, it does not seem likely that these effects will work against the complexity effect. Conglomerates and high-complexity conglomerates, on average, are large firms. High idiosyncratic volatility firms and short-sale constrained firms are usually small firms. However, Table 2 in the paper does show that conglomerates and especially high-complexity conglomerates have lower institutional ownership and higher analyst disagreement than single-segment firms with similar characteristics (size, age, market-to-book, etc.)

Table 3A runs the horse race between the Conglo dummy and the disagreement and short-sale constraints measures that are known to predict returns (using other complexity variables instead of the Conglo dummy yields similar results, not reported to save space). In columns two to four, I find that there is little overlap between the complexity effect and either the idiosyncratic volatility or turnover effect.[1,2] Controlling for either institutional ownership or relative short interest in columns six and seven makes the complexity effect stronger, though that is primarily an artefact of a restricted sample: the slope on the Conglo dummy is similar to the one reported in columns six and seven if I do not control for institutional ownership or relative short interest and only restrict the sample to firms with non-missing institutional ownership or relative short interest.

[1] Column two finds, consistent with Huang et al. (2010), that idiosyncratic volatility is insignificant in the presence of the reversal control. Therefore, in column three only, I omit the reversal control, which restores the significance of idiosyncratic volatility, but does not affect the (lack of) overlap between the idiosyncratic volatility effect and the complexity effect.

[2] Turnover can also serve as a disagreement measure, as Barinov, 2014, finds

Similarly, it seems as if controlling for analyst disagreement makes the complexity effect significantly smaller, but in fact the complexity effect is simply smaller for the subsample of firms with at least two non-stale analyst forecasts (which would be natural for any anomaly), and controlling for analyst disagreement in this subsample does not reduce the complexity effect further.

It is also interesting that neither of the control variables loses significance or is materially reduced in the presence of the Conglo dummy, which confirms the message of Table 3A that the complexity effect is largely orthogonal to other anomalies related to the Miller (1977) story. The different nature of the complexity effect is further confirmed by the kitchen sink regressions in the two rightmost columns in Table 3A, which use all five disagreement/short-sale constraints measures together, and the complexity effect still has the same magnitude and significance in their presence.[3]

Overall, Table 3A suggests that firm complexity is a special disagreement proxy, and the complexity effect is a special disagreement effect, since most high disagreement firms are small, and the disagreement effects of the Miller (1977) breed usually refer to overpricing of hard-to-trade, obscure firms. The complexity effect suggests that there is a special class of large, high-disagreement firms (conglomerates) that are also overpriced.

3 Complexity Effect and Limits to Arbitrage

Table 4A repeats the double sorts on complexity and residual institutional ownership (RInst) and complexity and idiosyncratic volatility (IVol) from Table 8 in the paper using NSeg (the number of segments with different two-digit SIC codes) and the RSZ measure

[3]Column eight controls for all variables except for relative short interest, because the short interest data start in 1988, making me lose the first decade of my sample, and requiring non-missing short interest alone makes my cross-sectional sample twice smaller.

(the variability of segment-level market-to-book) instead of Comp=1-HHI.

Panel A of Table 8 in the paper performed double sorts on Comp and RInst and found that the complexity effect is significant only in the bottom two RInst groups, reaching 59 bp per month, t-statistic 5.01, for firms in the bottom 30% in terms of RInst. This value of the complexity effect is almost five times larger than the one in the top RInst group. Panel A of Table 4A agrees that the complexity effect is confined in the bottom two RInst groups and is small and insignificant in the top RInst group. Panel A of Table 4A pegs the complexity effect in the bottom RInst group at 59-73 bp per month, close to the value in Panel A of Table 8 in the paper.

Panel B of Table 8 in the paper similarly concludes that the complexity effect exists only for the top 30% firms in terms of IVol, for which it stands at 46 bp per month, while being marginally insignificant in the bottom two IVol groups. In particular, Panel B of Table 8 in the paper highlights the extremely negative alpha of high IVol conglomerates, -74 bp per month.

Panel B of Table 4A finds that the complexity effect is indeed stronger for high IVol firms: double sorts that use NSeg or RSZ instead of Comp to measure complexity, estimate the complexity effect for high IVol firms to be 73 bp and 77 bp per month, respectively. The complexity effect in the other two IVol groups is smaller and close in its magnitude to what Panel B of Table 8 in the paper reports, but the alternative measure of complexity produce statistically significant complexity effect even for low IVol firms. As for the alpha of high IVol conglomerates, the double sorts on IVol and either NSeg or RSZ estimates it to be -101 bp and -102 bp per month, respectively.

Panels C and D present double sorts on complexity (NSeg or RSZ) and probability to be on special and Stambaugh et al. overpricing measure, respectively. The results in Panel C of Table 8 in the paper and Panel C of Table 4A are very similar, with two slight differences: first, in Panel C of Table 4A the complexity effect remains significant in the lowest probability to be on special group (and its magnitude changes from 20 bp per month in Panel C of Table 8 in the paper to 30 bp per month in Panel C of Table 4A). Second, in Panel C1 of Table 4A (NSeg sorts) the difference in the complexity effect between high and low probability to be on special firms becomes marginally insignificant (t-statistic 1.57).

The results in Panel D in Table 4A (double sorts on complexity and Stambaugh et al. overpricing measure) are somewhat stronger that those in Panel D of Table 8 in the paper. First, in Panel D1 of Table 4A (NSeg/overpricing sorts) the relation between overpricing and the complexity effect is more monotonic. Second, in Panel D2 (RSZ/overpricing sorts) the difference in the complexity effect between underpriced and overpriced firms is statistically significant at 46 bp per month, t-statistic 2.35 (as compared to 22 bp per month in Panel D of Table 8 in the paper). Third, the alphas of high complexity conglomerates in the overpriced firms subsample are at -48 and -57 bp per month in Panel D of Table 4A, as compared to -35 bp per month in Panel D of Table 8 in the paper.

Overall, Table 4A produces results very similar to the ones in Table 8 in the paper, suggesting that the strong relation between the complexity effect and limits to arbitrage is robust to using different complexity measures.

Table 5A confirms the results in Table 4A and in Table 8 in the paper using cross-sectional regressions. The cross-sectional regressions are performed separately in each residual institutional ownership (Panel A) or idiosyncratic volatility (Panel B) quartile. The rightmost column of each panel reports the difference in the regression coefficients between top and bottom quartiles.

Panel A uses the Conglo dummy, but in untabulated results I observe that the other three complexity measures also agree that the complexity effect is strong and significant in the bottom two institutional ownership quartiles, in both of which it has similar magnitude, declines by about a factor of two, but remains significant in the third quartile, and essentially disappears in the top institutional ownership quartile. The difference in the complexity effect between low and high institutional ownership subsamples is statistically significant irrespective of which of the four complexity measures I use. This behavior of the complexity effect is consistent with it being generated with the interaction of uncertainty/disagreement created by complexity and short-sale constraints (proxied by institutional ownership).

Panel B reports similar analysis using idiosyncratic volatility quartiles. Consistent with the hypothesis that the complexity effect is mispricing and thus is stronger for firms with higher limits to arbitrage, Panel B shows that the complexity effect is completely absent in the two lowest idiosyncratic volatility quartiles, is marginally significant at the 10% level in the third quartile and large (three times larger than in the third quartile) and strongly significant in the top idiosyncratic volatility quartile.

To sum up, Tables 4A and 5A consistently record that the complexity effect is significantly stronger for low (residual) institutional ownership firms and for high idiosyncratic volatility firms. The former evidence is supportive of the central hypothesis of the paper that firm complexity creates uncertainty/disagreement, and then the uncertainty/disagreement interacts with short-sale constraints to create overpricing as in Miller (1977). The latter evidence is consistent with the view that firm complexity is mispricing that is preserved only if limits to arbitrage are high enough.

4 Complexity Effect and Coinsurance

Hann, Ogneva, and Ozbas (2013) argue that conglomerates have lower cost of capital, because they have lower risk due to coinsurance between the segments. Hann et al. measure cost of capital as the weighted average of cost of equity and cost of debt, and define cost of equity as the result of solving for the discount rate that would set the discounted value of analyst forecasted cash flows to equity equal to the current stock price (implied cost of capital). When Hann et al. look at the cost of equity defined as average stock returns (which is exactly how my paper looks at expected returns), they find no relation between cost of capital and conglomerate status, in contrast to this paper, because Hann et al. do not control for the investment and profitability factors (CMA and RMW)

Hann et al. perform several cross-sectional tests to support the coinsurance hypothesis. They find that the lower cost of capital for conglomerates is more visible if the correlation between segment cash flows is lower, making it more likely that when one segment has a low cash flow realization, another one has a higher cash flow realization. They also find that conglomeration makes cost of capital lower for financially constrained firms, which have to rely more on internal funds and coinsurance.

In Table 6A, I perform the cross-sectional regressions of future returns on the Comp measure of complexity (sales concentration) and asset-pricing controls splitting the sample on measures of financial constraints (Panel A) and correlation between segment-level cash flows (Panel B1). The regressions are the same as in Table 4 in the paper and Table 5A. Using other complexity variables instead of Comp leaves the results qualitatively the same.

Panel A splits the sample according to whether the Kaplan and Zingales (1997), Whited and Wu (2006) or Hadlock and Pierce (2010) financial constraints measure is above or below median (the definitions of the measures are in Data Appendix). The financial constraints measures deliver a split message: the Hadlock-Pierce and Whited-Wu measures suggest that the complexity effect comes from financially constrained firms, consistent with the coinsurance explanation of Hann, Ogneva, and Ozbas (2013), and the Kaplan-Zingales index suggests otherwise.

In Panel B1 of Table 6A, I split the sample on cash flow correlations between the segments to verify if the complexity effect is stronger if the correlation is lower, which seems to be the ultimate test of the coinsurance explanation of the complexity effect. Following Hann et al., I define segment-level cash flows as average quarterly cash flows to single-segment firms with the same two-digit SIC code, and compute cash flows correlation between two segments as the correlation between the average cash flows of the two respective industries in the most recent 10 years. The correlations are then weighted by the weight of the segment sales in the total sales of the conglomerate according to the formula in Data Appendix, thus creating a cash flow correlation measure for each conglomerate. The cross-segment cash flows correlation is defined only for multi-segment firms, which makes the sample size in Panel B1 significantly smaller (all single-segment firms are dropped from Panel B1) and makes me use the HiComp dummy instead of the Comp measure, as in the rightmost column of Table 4 in the paper.

According to Panel B1, the negative and barely significant relation between complexity and future returns is visible in both low and high cross-segment correlation groups (since Panel B1 is restricted to conglomerates only, its results also corroborate the rightmost column of Table 4 in the paper, which finds that high-complexity conglomerates have lower expected returns than low-complexity conglomerates). While the slope on the HiComp variable is indeed twice more negative in the low cross-segment correlation group, as Hann et al. would predict, the difference between the groups is not close to being statistically significant, which suggests that the complexity effect is unlikely to be caused by coinsurance.

A recent paper by Farre-Mensa and Ljungqvist (2016) casts doubt on the popular financial constraints measures used in Hann et al. and Panel A above, and concludes that distress measures (for example, credit rating) tend to measure financial constraints better than the specially designed financial constraints measures.

Panel B2 of Table 6A splits the sample on credit rating, into firms with investment-grade debt (IG, S&P credit rating of BBB or better), firms with junk bonds (Junk, S&P credit rating below BBB), and non-rated firms. Investment-grade firms have smaller financial constraints than firms with junk debt or non-rated firms. The relation between financial constraints of the latter two groups is less clear: on the one hand, non-rated firms have the additional potential hurdle of entering the public debt market, which they have not tapped for a while or at all, on the other hand, some non-rated firms are in good financial shape, while all firms with junk bonds are, to some extent, distressed.

Panel B2 reveals that the complexity effect exists only for non-rated firms, for which it is significantly stronger than for either investment-grade firms or junk bonds issuers. The former difference is consistent with the coinsurance argument in Hann et al., who argue that conglomerates have lower risk because they can transfer money between segments, and this ability is more valuable for financially constrained firms.

However, Panel B2 also reveals that the complexity effect flips its sign for junk bond issuers subsample, which is inconsistent with the Hann et al. story above. The relation between complexity and future returns in this subsample is significantly positive, and it is also significantly more positive than the insignificantly negative relation between complexity and future returns for investment-grade firms.[4]

Overall, Table 6A does not exclude the possibility that the complexity effect can be explained by lower risk of conglomerates coming from coinsurance. Several results in Table 6A are consistent with this interpretation - but Table 6A also contains several results that are inconsistent with the coinsurance story. Most importantly, the complexity effect is not significantly related to the correlation between segment-level cash flows, which determines the possibility of coinsurance. Another troubling fact for the coinsurance explanation is the "wrong" sign of the complexity effect in the junk-rated subsample.

5 Complexity Effect and Diversification Discount

The existence of the complexity effect seems at odds with the existence of the diversification discount of Berger and Ofek (1995). The diversification discount is usually defined as the negative difference between the actual and imputed market-to-book (or other valuation ratio) of conglomerates and single-segment firms[5]

If the complexity effect implies that conglomerates have lower expected returns (cost of equity), as Hann, Ogneva, and Ozbas (2013) suggest, then conglomerates should be trading at higher valuation multiples, and the diversification discount says the opposite. One way to reconcile the two is to argue that diversification hurts cash flows, and the negative effect in the numerator of the discounted cash flows formula exceeds the positive effect in the denominator (the complexity effect). Another way would be to argue that

[4]The lack of the complexity effect among junk bond issuers suggests that the complexity effect is not driven by distressed firms and downgrades, while, according to Avramov, Chordia, Jostova, Philipov (2013), several other disagreement effects, like the Diether et al. (2002) analyst disagreement effect, depend on whether firms with credit ratings of C and below are included in the sample.

[5]Imputed market-to-book is the weighted average of segment-level market-to-books, where weights are the shares of the segment-level assets in total conglomerate assets, and segment-level market-to-book is the average market-to-book of all single-segment firms in the same industry as the segment (in my case, with the same two-digit SIC code).

the complexity effect constitutes the resolution of mispricing, i.e., the slow adjustment of conglomerate stock prices to the fact that diversification hurts cash flows: investors start with too optimistic beliefs about complex firms cash flows, and those beliefs are gradually updated downwards, causing both a sequence of negative alphas and, as a result, lower valuation multiples of conglomerates.

Lamont and Polk (2001) link the level of diversification discount to expected returns in a way that seems to be at odds with Hann, Ogneva, and Ozbas (2013). Lamont and Polk argue that, among diversified firms, higher diversification discount (lower valuation multiples) corresponds to higher expected returns. Lamont and Polk, however, do not find significant difference in expected returns between diversified and focused (i.e., single-segment) firms, which means that their observation about expected returns cannot explain why diversification discount is positive on average, it can only explain why it is different for different diversified firms.

The Lamont and Polk result can be behind the results in this paper if firm complexity, which is negatively related to future returns, is negatively associated with diversification discount, which is, in turn, positively related to expected returns. A priori, such relation does not seem plausible, since firm complexity seems to suggest greater diversification (and thus, allegedly, greater diversification discount).

Panel A excludes all single-segment firms and splits all conglomerates in the sample into the ones with low diversification discount (the difference between actual and imputed market-to-book is slightly negative or positive) and the one with high diversification discount (the same difference is very negative). The cutoff for the split is the median value of diversification discount in a given year. The regressions of future returns on the HiComp dummy and standard controls are then performed separately in each diversification discount group.

Panel A shows that the complexity effect is concentrated in the group of conglomerates with larger diversification discount, which suggests that the complexity effect and the effect of diversification on expected returns in Lamont in Polk (2001) are two different phenomena. First, controlling for diversification discount by splitting the sample into two relatively uniform groups does not make the complexity effect weaker (in fact, it is more significant than in the rightmost column of Table 4 in the paper, which estimates the complexity effect for conglomerate-only subsamples). Second, the prevalence of the complexity effect (low returns to conglomerates) among conglomerates with high expected returns (according to Lamont and Polk) suggests that the complexity effect is not an discount rate effect, but rather a gradual resolution of overpricing, which happens for value-destroying conglomerates when investors do not initially understand the extent of the value destruction. Under this mispricing assumption, the concentration of the complexity effect among conglomerates with greater diversification discount becomes natural.

Panel B of Table 7A runs a more traditional horse race between complexity and diversification discount by putting into one regression the measure of diversification discount and the high complexity dummies from Table 4 in the paper and Table 2A. As in Panel A of Table 7A, the sample is restricted to conglomerates only.

Panel B shows that complexity and diversification discount, if anything, strengthen each other when used in the same regression. All high complexity dummies in Panel B are statistically significant at the 10% level (in Table 2A, which runs similar regressions without the diversification discount control in the right columns of each panel, the slope on HiSeg dummy is small and insignificant) and, compared to Table 4 in the paper and Table 2A, the slopes on HiComp and HiRSZ dummies increase by 25% and 47% after controlling for diversification discount and its relation to expected returns, and the slope on HiSeg dummy almost quadruples. Also, the magnitude of diversification discount is strongly and positively related to expected returns after controlling for conglomerate complexity, implying that the result of Lamont and Polk holds in the updated sample and is not diminished by controlling for complexity.

Mitton and Vorkink (2010) suggest an explanation of the positive relation between diversification discount and expected returns in Lamont and Polk (2001). Mitton and Vorkink argue that some investors have lottery preferences and are willing to pay higher prices for and accept lower expected returns to stocks with positive idiosyncratic skewness. Within the conglomerate, idiosyncratic skewness is diversified away, and that leads to higher expected returns and lower valuations.

Panel C tests the hypothesis that skewness can be related to the complexity effect by splitting firms in my sample (both conglomerates and single-segment firms) on their return skewness. Again, a priori higher complexity should imply greater diversification, and in the Mitton and Vorkink world that leads to lower skewness and higher, not lower future returns. Yet, Panel C tests whether destroying skewness further by creating a complex conglomerate would matter more if the firms have enough skewness to be destroyed in the first place.

I perform the regression of future returns on the Comp measure and standard controls and do not find any difference in the complexity effect between high and low skewness subsamples. In both subsamples, Comp is negative and significant, and it is slightly more negative in the high skewness sample, suggesting that the destruction of skewness by conglomeration cannot weaken the complexity effect, even though the destruction of skewness is supposed to work against the complexity effect.

6 Complexity Effect and Pricing of Financial Constraints

It has long been believed (see, e.g., Livdan et al., 2009 and references therein) that financially constrained firms should have higher expected returns due to their inflexibility and inability to borrow to absorb large cash flow shocks. Hann et al. (2013) argue that conglomerates are less risky than single-segment firms, and the difference in risk, stemming from coinsurance, is stronger if one looks at financially constrained conglomerates and equally constrained single-segment firms.

The empirical evidence that financial constraints are priced is mixed. The literature, starting with Lamont et al. (2001), shows that financially constrained firms do move together (which suggests existence of a common risk loading for them), but have lower, not higher expected returns.

In Table 8A, I form financial constraints factors by sorting firms into quintiles on financial constraints measures from Panel A of Table 6A and taking the high-minus-low return spread as a financial constraints factor. Since distress measures are also likely to be linked to financial constraints, I also sort firms on credit rating and expected default frequency (EDF) from Bharath and Shumway (2008).

Panel A of Table 8A reports alphas from the five-factor Fama and French (2015) model augmented with one of the financial constraints factors (as indicated in the column heading), and Panel B collects the betas with respect to the financial constraint factor. The left-hand side variable is the zero-minus-high complexity portfolio from sorts on the 1-HHI measure (Comp).

Since coinsurance between the divisions, internal capital size, and size all indicate that conglomerates are less financially constrained than single-segment firms, I expect the zero-minus-high complexity portfolio (long in single-segment firms and short in conglomerates with complexity above median) to load positively on high-minus-low financial constraints factors. If those all had positive five-factor alphas, I would also predict that the positive loadings on them would make the alphas of the zero-minus-high complexity portfolio smaller.

Panel B of Table 8A shows that loadings of the zero-minus-high complexity portfolio on the financial constraints factors are usually significantly negative, with the only exception being the factor based on EDF sorts, which does produce significantly positive loadings. However, Panel A reveals that controlling for the EDF factor does not impact the alpha of the zero-minus-high complexity portfolio, because the five-factor alpha of the EDF factor (not tabulated) is small and insignificant.

The only factor in Panel A that seems to reduce somewhat the alpha of the zero-minus-high complexity portfolio (by 8-12 bp per month) is the financial constraints factor based on the Kaplan and Zingales (1997) measure, KZ. However, this factor reduces the alpha of the zero-minus-high complexity portfolio in a counterintuitive fashion: Panel B reveals that the zero-minus-high complexity portfolio loads negatively on KZ, and KZ has negative rather than positive five-factor alpha (not tabulated), thus the reduction in the alpha of the zero-minus-high complexity portfolio. The negative alpha of KZ is consistent with what Lamont et al. (2001) find in an earlier sample, but the negative alpha of KZ suggests that financially constrained firms are less risky, which is counterintuitive.

Li (2011) argues that the logic of Livdan et al. (2009) that financial constraints increase the risk of the firm by making it more inflexible applies primarily to firms with high R&D expenses, which have a lot of value tied up in non-pledgable and hard-to-sell growth options. Consistent with that, Li (2011) finds that sorting on financial constraints firms with R&D above median produces a positive relation between financial constraints and expected returns, in contrast to negative/ambiguous relation in the full sample.

In the last three columns of Table 8A, I form financial constraints factors using only firms with R&D-to-sales ratio above the median among all firms with non-zero R&D. Panel B presents the betas and finds that even with this modification the financial constraint betas of the zero-minus-high complexity portfolio are negative (suggesting that conglomerates do not have lower risk coming from non-binding financial constraints). Consistent with Li (2011), the modified financial constraints factors have positive alphas (not tabulated) in my sample period, so the negative betas of the zero-minus-high complexity portfolio in Panel B convert to slightly higher alphas in the last three rows of Panel A than in the very first row (the five-factor alphas).

The general conclusion from Table 8A is that lower financial constraints are unlikely to be an explanation of why conglomerates have lower expected returns than single-segment firms, mostly because I fail to find, controlling for the five Fama-French factors, a positive relation between the zero-minus-high complexity portfolio and the high-minus-low financial constraints return spreads.

7 Complexity Effect and Investor Sentiment

In their seminal paper, Baker and Wurgler (2006) develop an index of market-wide sentiment and use it to predict returns to several anomalies-based portfolios. Baker and Wurgler argue that high sentiment leads to overvaluation of hard-to-value firms and thus high sentiment periods predict low returns to such firms going forward. For example, Baker and Wurgler find that their sentiment index is negatively related to future returns of high-minus-low portfolio based on the idiosyncratic volatility effect of Ang et al. (2006):

following high sentiment periods, high volatility firms become overpriced and then underperform.

The same argument can be made about high complexity conglomerates or conglomerates in general: they are hard-to-value and will be overpriced following waves of positive sentiment. In Panel A of Table 9A, I perform univariate regressions of complexity-sorted portfolios on lagged sentiment indicator and then on its version orthogonalized to macroeconomic variables, $Sent^{\perp}_{t-1}$[6] The prediction is that conglomerates have a negative slope on $Sent_{t-1}$ or $Sent^{\perp}_{t-1}$, single-segment firms have a positive, or at least, less negative slope, and the zero-minus-high complexity portfolio that captures the complexity effect thus should have a positive slop on sentiment.

Panel A of Table 9A finds the opposite: the relation between returns to high-complexity conglomerates and past sentiment is negative, but insignificantly so, but the relation of single-segment firms with past sentiment is even more negative and significant, probably because single-segment firms are smaller, and small firms load negatively on past sentiment, as Baker and Wurgler (2006) show. The zero-minus-high complexity portfolio has insignificantly negative rather than positive relation to lagged sentiment.

Panel B attempts to control for the business cycle variables from Table 10 in the paper, to make sure that the negative loadings on sentiment in Panel A do not equate to lower risk premium in good times. The loadings of complexity-sorted portfolios indeed become zero rather than negative, but the loading of the zero-minus-high complexity portfolio on past sentiment in Panel B is even more negative in Panel A.

I conclude that mispricing of conglomerates does not seem to be driven by waves of sentiment, most likely because conglomerates are large and stable firms.

[6]Both sentiment variables come from the website of Jeffrey Wurgler at https://pages.stern.nyu.edu/~jwurgler/.

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Table 1A. Firm Complexity and Expected Returns: Portfolio Sorts

The table sorts firms into three groups on firm complexity - the Zero group includes all single-segment firms, the Low/High group includes conglomerates with complexity below/above median. Panel A measures firm complexity as the number of business segments with different two-digit SIC codes. Panel B uses the RSZ complexity measure, which is the standard deviation of asset-weighted imputed segment market-to-books divided by the equal-weighted average imputed market-to-book of the segments. Conglomerates are defined as firms with business segments in more than one industry, industries are defined using two-digit SIC codes. Single-segment firms are firms that report business segments in only one industry on Compustat segment files.

Panels A1 and B1 report the alphas of the complexity groups and the differences between them using several models: the five-factor Fama-French (2015) model (α_{FF5}), the three-factor Fama-French (1993) model (FF3) augmented with the profitability/investment factor from the FF5 model ($\alpha_{FF3+RMW}/\alpha_{FF3+RMW}$), and the FF5 model augmented with the momentum factor ($\alpha_{FF5+MOM}$). The last two rows of the left part add the dummy for post-SFAS131 period (1 in 1999-2016, 0 in 1978-1998) to the FF5 model and present the FF5 alpha pre-SFAS131 (the intercept) and the change in the alpha post-SFAS131 (the slope on the dummy). Panels A2 and B2 report the factor betas of the complexity groups from the FF5 model.

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 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A1. Number of Segments and Alphas

	One	Two	3+	1-3+	1-2	2-3+
α_{FF5}	0.186	-0.047	-0.167	0.353	0.232	0.124
t-stat	*2.97*	*-0.92*	*-3.05*	*3.93*	*3.21*	*1.84*
$\alpha_{FF5+MOM}$	0.230	-0.025	-0.120	0.349	0.255	0.098
t-stat	*3.53*	*-0.48*	*-2.26*	*3.89*	*3.66*	*1.44*
$\alpha_{FF3+CMA}$	0.036	0.028	-0.096	0.132	0.009	0.127
t-stat	*0.56*	*0.56*	*-1.74*	*1.33*	*0.11*	*2.00*
$\alpha_{FF3+RMW}$	0.157	-0.013	-0.107	0.263	0.170	0.097
t-stat	*2.68*	*-0.25*	*-1.96*	*3.11*	*2.38*	*1.40*
$\alpha_{pre-SFAS}$	0.150	-0.034	-0.196	0.346	0.184	0.162
t-stat	*2.11*	*-0.56*	*-2.82*	*2.94*	*1.84*	*1.93*
$\Delta\alpha_{post-SFAS}$	0.077	-0.027	0.063	0.014	0.104	-0.082
t-stat	*0.73*	*-0.28*	*0.62*	*0.09*	*0.74*	*-0.60*

Panel A2. Number of Segments and FF5 Betas

	One	Two	3+	1-3+	1-2	2-3+
β_{MKT}	0.962	0.998	1.085	-0.123	-0.036	-0.087
t-stat	*49.6*	*57.9*	*68.8*	*-4.66*	*-1.57*	*-4.73*
β_{SMB}	0.021	-0.028	-0.098	0.119	0.049	0.071
t-stat	*0.72*	*-1.10*	*-3.65*	*3.13*	*1.16*	*2.18*
β_{HML}	-0.103	-0.030	0.032	-0.135	-0.073	-0.059
t-stat	*-2.94*	*-0.86*	*0.82*	*-2.59*	*-1.85*	*-1.45*
β_{CMA}	-0.111	0.131	0.232	-0.342	-0.241	-0.104
t-stat	*-1.90*	*2.24*	*3.73*	*-5.27*	*-3.92*	*-1.54*
β_{RMW}	-0.320	0.159	0.152	-0.472	-0.479	0.007
t-stat	*-7.50*	*3.93*	*3.33*	*-8.72*	*-8.82*	*0.14*

Panel B1. RSZ Measure and Alphas

	Zero	Low	High	Z-H	Z-L	L-H
α_{FF5}	0.179	-0.103	-0.310	0.488	0.282	0.207
t-stat	*2.63*	*-1.14*	*-2.76*	*3.40*	*2.33*	*1.65*
$\alpha_{FF5+MOM}$	0.210	-0.075	-0.295	0.505	0.285	0.220
t-stat	*2.91*	*-0.82*	*-2.57*	*3.43*	*2.30*	*1.73*
$\alpha_{FF3+CMA}$	0.055	-0.051	-0.206	0.261	0.107	0.155
t-stat	*0.89*	*-0.54*	*-1.81*	*1.76*	*0.87*	*1.24*
$\alpha_{FF3+RMW}$	0.152	-0.067	-0.267	0.419	0.219	0.200
t-stat	*2.42*	*-0.71*	*-2.43*	*3.04*	*1.88*	*1.55*
$\alpha_{pre-SFAS}$	0.170	-0.237	-0.413	0.583	0.407	0.176
t-stat	*2.42*	*-1.52*	*-2.07*	*2.39*	*2.32*	*0.85*
$\Delta\alpha_{post-SFAS}$	0.022	0.121	0.287	-0.266	-0.099	-0.157
t-stat	*0.22*	*0.63*	*1.33*	*-1.08*	*-0.46*	*-0.63*

Panel B2. RSZ Measure and FF5 Betas

	Zero	Low	High	Z-H	Z-L	L-H
β_{MKT}	0.963	1.046	1.054	-0.091	-0.084	-0.008
t-stat	*49.5*	*49.2*	*66.0*	*-3.05*	*-3.26*	*-0.32*
β_{SMB}	0.021	-0.101	-0.012	0.033	0.122	-0.089
t-stat	*0.71*	*-3.44*	*-0.49*	*0.80*	*2.99*	*-2.60*
β_{HML}	-0.104	-0.036	0.073	-0.177	-0.068	-0.109
t-stat	*-2.99*	*-0.72*	*2.45*	*-3.78*	*-1.13*	*-2.00*
β_{CMA}	-0.109	0.180	0.196	-0.305	-0.289	-0.015
t-stat	*-1.87*	*2.49*	*4.08*	*-4.47*	*-3.64*	*-0.18*
β_{RMW}	-0.320	0.102	0.264	-0.584	-0.422	-0.162
t-stat	*-7.51*	*2.19*	*6.93*	*-9.23*	*-8.57*	*-3.27*

Table 2A. Conglomerate Complexity and Expected Returns

The table presents firm-level cross-sectional regressions of DGTW-adjusted returns on dummy variables for firm complexity being above/below median and the same control variables as in Tables 4. The left/right panel uses number of segments/the RSZ measure to measure firm complexity. HiSeg/LoSeg variable is 1 if the number of the firm's segments in industries with different two-digit SIC codes is more than/equal to 2, and 0 otherwise. HiRSZ/LoRSZ variable is 1 if the RSZ measure is above/below median, and 0 otherwise. The median complexity is determined separately in each quarter using only conglomerates. Conglomerates are defined as firms with business segments in more than one industry, industries are defined using two-digit SIC codes. Conglo is 1 if the firm is a conglomerate, and 0 otherwise. The first two columns of each panel use the full sample of firms on Compustat segment files, the third column looks at conglomerates only. 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 2016. The sample excludes stocks priced below $5.

Panel A. Number of Segments

	HiLo	**CongHi**	**CongOnly**
Beta	0.094	0.094	0.057
t-stat	*0.92*	*0.92*	*0.52*
Size	0.000	0.000	0.000
t-stat	*-0.19*	*-0.19*	*0.35*
MB	-0.038	-0.038	-0.045
t-stat	*-4.50*	*-4.50*	*-3.17*
Mom	-0.092	-0.092	-0.083
t-stat	*-1.67*	*-1.67*	*-0.94*
Rev	-0.048	-0.048	-0.049
t-stat	*-10.6*	*-10.6*	*-9.81*
Inv	-1.032	-1.032	-1.088
t-stat	*-4.26*	*-4.26*	*-3.92*
Prof	0.507	0.507	0.793
t-stat	*3.42*	*3.42*	*4.10*
HiSeg	-0.143	-0.037	-0.028
t-stat	*-2.40*	*-0.73*	*-0.56*
LoSeg	-0.106		
t-stat	*-1.99*		
Conglo		-0.106	
t-stat		*-1.99*	

Panel B. Zingales Measure

	HiLo	**CongHi**	**CongOnly**
Beta	0.094	0.094	0.046
t-stat	*0.92*	*0.92*	*0.41*
Size	0.000	0.000	0.000
t-stat	*-0.31*	*-0.30*	*0.28*
MB	-0.035	-0.035	-0.048
t-stat	*-4.27*	*-4.27*	*-3.24*
Mom	-0.089	-0.089	-0.071
t-stat	*-1.62*	*-1.62*	*-0.84*
Rev	-0.047	-0.047	-0.047
t-stat	*-10.6*	*-10.6*	*-9.67*
Inv	-1.042	-1.042	-1.193
t-stat	*-4.19*	*-4.19*	*-3.74*
Prof	0.500	0.500	0.848
t-stat	*3.37*	*3.37*	*4.28*
HiRSZ	-0.180	-0.103	-0.094
t-stat	*-2.79*	*-2.05*	*-1.84*
LoRSZ	-0.078		
t-stat	*-1.41*		
Conglo		-0.077	
t-stat		*-1.40*	

Table 3A. Complexity Effects and Additional Controls

The table presents cross-sectional regressions of DGTW-adjusted returns on complexity measures and controls. DGTW adjustment (described in detail in Data Appendix) adjusts returns for size, market-to-book, and momentum. The complexity measures and standard control variables are defined in the heading of Table 4 in the paper. Additional controls include idiosyncratic volatility (IVol), analyst forecast dispersion (Disp), stock turnover (Turn, dollar volume over market cap), institutional ownership (IO), and relative short interest (RSI). RSI is available from January 1988 to December 2016. 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 2016. The sample excludes stocks priced below $5.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Beta	0.093	0.105	0.107	0.122	0.191	0.105	0.350	0.184	0.307
t-stat	*0.92*	*1.08*	*1.16*	*1.09*	*2.02*	*0.87*	*2.39*	*1.78*	*2.34*
Size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t-stat	*-0.34*	*0.17*	*-2.32*	*-2.69*	*2.12*	*-1.21*	*0.06*	*-3.95*	*-3.11*
MB	-0.038	-0.037	-0.030	-0.006	-0.023	-0.019	-0.025	-0.007	0.007
t-stat	*-4.52*	*-4.55*	*-3.93*	*-0.46*	*-1.98*	*-2.30*	*-2.63*	*-0.50*	*0.57*
Mom	-0.092	-0.097	-0.135	-0.133	-0.104	-0.038	-0.111	-0.209	-0.137
t-stat	*-1.68*	*-1.67*	*-2.27*	*-2.00*	*-1.84*	*-0.67*	*-1.63*	*-2.97*	*-1.65*
Rev	-0.048	-0.049		-0.037	-0.049	-0.027	-0.041	-0.032	-0.022
t-stat	*-10.6*	*-11.0*		*-7.83*	*-10.6*	*-6.29*	*-7.65*	*-7.28*	*-4.38*
Inv	-1.032	-1.024	-0.967	-0.909	-0.980	-0.742	-0.442	-0.649	-0.226
t-stat	*-4.26*	*-4.27*	*-4.22*	*-3.28*	*-3.99*	*-3.19*	*-1.62*	*-2.59*	*-0.75*
Prof	0.509	0.499	0.459	0.315	0.484	0.486	0.439	0.419	0.296
t-stat	*3.44*	*3.42*	*3.23*	*1.88*	*3.09*	*3.06*	*2.20*	*2.40*	*1.39*
IVol		-2.849	-6.144					-8.719	-5.639
t-stat		*-0.90*	*-2.02*					*-2.36*	*-1.31*
Disp				-0.356				-0.227	-0.149
t-stat				*-4.39*				*-2.82*	*-1.49*
Turn					-3.833			-0.526	1.853
t-stat					*-4.87*			*-0.65*	*1.99*
IO						-0.325		-0.403	-1.022
t-stat						*-3.38*		*-0.75*	*-2.01*
RSI							-9.437		-9.000
t-stat							*-6.48*		*-7.11*
Conglo	-0.121	-0.113	-0.115	-0.079	-0.124	-0.156	-0.211	-0.111	-0.148
t-stat	*-3.01*	*-2.97*	*-3.00*	*-1.85*	*-3.08*	*-3.90*	*-3.55*	*-2.56*	*-2.62*

Table 4A. Complexity Effects and Limits to Arbitrage: Portfolio Sorts

The table reports five-factor Fama-French (2015) alphas in the double sorts on complexity and residual institutional ownership, RInst (Panel A) or idiosyncratic volatility, IVol (Panel B). The complexity groups (names in column headings) are the Low group, which includes all single-segment firms, and the Med/High groups, which include conglomerates with complexity below/above median. RInst/IVol groups (names in row headings) are top 30%, middle 40%, bottom 30%. The breakpoints for the RInst/IVol groups are determined using NYSE only firms. RInst is institutional ownership orthogonalized to size. 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 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Firm Complexity, Expected Returns and Institutional Ownership

A1. Number of Segments					A2. RSZ Complexity Measure				
	Zero	**Low**	**High**	**Z-H**		**Zero**	**Low**	**High**	**Z-H**
Low	0.295	-0.068	-0.433	0.728	**Low**	0.297	-0.304	-0.296	0.594
t-stat	*2.96*	*-0.69*	*-3.61*	*5.14*	**t-stat**	*2.99*	*-1.72*	*-3.51*	*4.49*
RInst2	0.213	-0.166	-0.158	0.372	**RInst2**	0.214	-0.107	-0.214	0.429
t-stat	*2.85*	*-1.82*	*-1.28*	*2.66*	**t-stat**	*2.86*	*-0.91*	*-2.22*	*3.43*
High	0.065	0.045	-0.035	0.100	**High**	0.070	0.043	-0.028	0.097
t-stat	*0.76*	*0.46*	*-0.38*	*0.86*	**t-stat**	*0.81*	*0.40*	*-0.30*	*0.74*
L-H	-0.231	0.109	0.398	0.628	**L-H**	-0.228	0.347	0.269	0.497
t-stat	*-1.98*	*0.78*	*2.39*	*3.81*	**t-stat**	*-1.94*	*1.65*	*2.17*	*3.11*

Panel B. Firm Complexity, Expected Returns and Idiosyncratic Volatility

B1. Number of Segments					B2. RSZ Complexity Measure				
	Zero	**Low**	**High**	**Z-H**		**Zero**	**Low**	**High**	**Z-H**
Low	0.104	-0.071	-0.153	0.257	**Low**	0.095	-0.021	-0.160	0.255
t-stat	*1.26*	*-0.98*	*-2.36*	*2.55*	**t-stat**	*1.15*	*-0.26*	*-2.39*	*2.50*
IVol2	0.151	-0.011	-0.121	0.272	**IVol2**	0.154	-0.130	-0.180	0.334
t-stat	*1.93*	*-0.13*	*-1.02*	*1.87*	**t-stat**	*1.98*	*-1.11*	*-1.67*	*2.51*
High	-0.274	-0.667	-1.008	0.734	**High**	-0.250	-0.745	-1.023	0.773
t-stat	*-1.77*	*-3.40*	*-3.31*	*2.23*	**t-stat**	*-1.61*	*-2.98*	*-3.35*	*2.15*
H-L	0.378	0.595	0.855	0.477	**H-L**	0.345	0.725	0.863	0.518
t-stat	*2.06*	*2.70*	*2.63*	*1.37*	**t-stat**	*1.83*	*2.66*	*2.72*	*1.37*

Panel C. Firm Complexity, Expected Returns and Probability to Be on Special

C1. Number of Segments

	Zero	Low	High	Z-H
Low	0.176	-0.098	-0.121	0.297
t-stat	*2.30*	*-1.13*	*-1.43*	*2.35*
Spec2	0.182	-0.046	-0.253	0.435
t-stat	*2.11*	*-0.42*	*-1.60*	*2.75*
High	0.096	-0.517	-0.536	0.633
t-stat	*0.66*	*-3.93*	*-3.23*	*2.84*
H-L	0.080	0.419	0.415	0.336
t-stat	*0.56*	*2.81*	*2.38*	*1.57*

C2. RSZ Complexity Measure

	Zero	Low	High	Z-H
Low	0.176	-0.105	-0.120	0.296
t-stat	*2.31*	*-1.03*	*-1.25*	*2.29*
Spec2	0.190	-0.081	-0.337	0.527
t-stat	*2.18*	*-0.53*	*-3.15*	*4.26*
High	0.097	-0.690	-0.635	0.732
t-stat	*0.66*	*-4.86*	*-4.20*	*3.87*
H-L	0.079	0.585	0.515	0.436
t-stat	*0.56*	*3.42*	*3.32*	*2.14*

Panel D. Firm Complexity, Expected Returns and Composite Overpricing Measure

D1. Number of Segments

	Zero	Low	High	Z-H
Low	0.183	0.132	0.035	0.148
t-stat	*2.14*	*1.51*	*0.31*	*0.89*
Over2	0.352	-0.142	-0.143	0.495
t-stat	*4.19*	*-1.37*	*-1.57*	*3.73*
High	-0.016	-0.412	-0.475	0.460
t-stat	*-0.10*	*-2.83*	*-2.77*	*2.44*
H-L	0.198	0.544	0.510	0.311
t-stat	*1.03*	*2.91*	*2.68*	*1.32*

D2. RSZ Complexity Measure

	Zero	Low	High	Z-H
Low	0.184	0.041	0.082	0.101
t-stat	*2.16*	*0.39*	*0.95*	*0.73*
Over2	0.350	0.042	-0.367	0.717
t-stat	*4.18*	*0.48*	*-3.70*	*5.06*
High	-0.014	-0.479	-0.573	0.558
t-stat	*-0.09*	*-2.90*	*-3.53*	*3.25*
H-L	0.198	0.521	0.655	0.457
t-stat	*1.03*	*2.39*	*3.89*	*2.35*

Table 5A. Complexity Effects and Limits to Arbitrage: Cross-Sectional Regressions

The table presents cross-sectional regressions of DGTW-adjusted returns on the conglomerate dummy (Conglo) and controls, performed separately in each institutional ownership (Panel A) or idiosyncratic volatility (Panel B) quartile. DGTW adjustment (described in detail in Data Appendix) adjusts returns for size, market-to-book, and momentum. The control variables are defined in the heading of Table 4. 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 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Institutional Ownership Quartiles						**Panel B. Idiosyncratic Volatility Quartiles**					
	Low	**2**	**3**	**High**	**L-H**		**Low**	**2**	**3**	**High**	**H-L**
Beta	-0.118	0.261	0.088	0.191	-0.311	**Beta**	0.167	0.207	0.045	-0.083	0.250
t-stat	*-0.75*	*2.13*	*0.69*	*1.49*	*-3.17*	**t-stat**	*1.42*	*1.95*	*0.43*	*-0.75*	*1.93*
Size	0.000	0.000	0.000	0.000	0.000	**Size**	0.000	0.000	0.000	0.000	0.000
t-stat	*-4.96*	*-3.68*	*-3.23*	*-4.23*	*-1.10*	**t-stat**	*1.33*	*-1.61*	*-3.19*	*-3.67*	*3.71*
MB	0.002	-0.028	-0.021	0.017	-0.015	**MB**	-0.002	0.011	-0.004	-0.040	0.039
t-stat	*0.20*	*-2.17*	*-1.65*	*1.62*	*-0.85*	**t-stat**	*-0.12*	*0.99*	*-0.38*	*-3.42*	*2.02*
Mom	0.125	-0.216	-0.413	-0.078	0.207	**Mom**	-0.191	-0.051	-0.001	-0.416	0.225
t-stat	*0.92*	*-1.80*	*-5.01*	*-0.83*	*1.24*	**t-stat**	*-1.51*	*-0.62*	*-0.01*	*-3.47*	*1.19*
Rev	-0.012	-0.022	-0.030	-0.036	0.024	**Rev**	-0.037	-0.041	-0.039	-0.058	0.021
t-stat	*-2.05*	*-3.89*	*-6.44*	*-6.99*	*4.50*	**t-stat**	*-5.14*	*-8.73*	*-8.69*	*-10.52*	*2.51*
Inv	-0.907	-1.178	-0.845	-0.500	-0.415	**Inv**	-0.434	-0.312	-0.743	-1.886	1.451
t-stat	*-2.57*	*-3.59*	*-2.66*	*-1.95*	*-1.29*	**t-stat**	*-1.31*	*-1.53*	*-2.87*	*-5.41*	*3.30*
Prof	0.357	0.490	0.374	0.288	0.094	**Prof**	0.388	0.444	0.620	0.398	-0.010
t-stat	*1.75*	*2.40*	*1.97*	*1.72*	*0.53*	**t-stat**	*3.02*	*3.28*	*3.77*	*1.79*	*-0.04*
Conglo	-0.366	-0.411	-0.213	-0.039	-0.316	**Conglo**	-0.018	-0.022	-0.089	-0.301	0.283
t-stat	*-3.18*	*-4.47*	*-2.83*	*-0.66*	*-2.84*	**t-stat**	*-0.35*	*-0.46*	*-1.33*	*-2.69*	*2.41*

Table 6A. Complexity Effects across Financial Constraints, Segment Correlation, and Credit Rating Groups

The table presents cross-sectional regressions of DGTW-adjusted returns on the Comp measure and controls, performed separately in each financial constraints/segment correlation/credit rating group (above/below median). DGTW adjustment (described in detail in Data Appendix) adjusts returns for size, market-to-book, and momentum. Segment correlation is the sales-weighted sum of pairwise segment correlations estimated using cash flows of single-segment firms in the industry of the segments over a prior 10-year period. Credit rating groups include firms with investment-grade rating (BBB or better), firms with junk-bond rating (below BBB) and non-rated firms. The Comp measure and control variables are defined in the heading of Table 4 in the paper. 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 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Cross-Sectional Regressions in Financial Constraints Groups

A1. Hadlock-Pierce Index				A2. Whited-Wu Index				A3. Kaplan-Zingales Index			
	Low	**High**	**H-L**	**WW**	**Low**	**High**	**H-L**	**KZ**	**Low**	**High**	**H-L**
Beta	0.066	0.151	-0.085	**Beta**	0.109	0.100	0.009	**Beta**	0.095	0.075	0.019
t-stat	*0.58*	*1.64*	*-1.07*	**t-stat**	*1.01*	*1.09*	*0.13*	**t-stat**	*0.98*	*0.76*	*0.33*
Size	0.000	0.000	0.000	**Size**	0.000	0.000	0.000	**Size**	0.000	0.000	0.000
t-stat	*-0.68*	*-3.11*	*3.10*	**t-stat**	*0.47*	*-2.05*	*2.06*	**t-stat**	*-0.97*	*-1.42*	*0.98*
MB	0.006	-0.046	0.051	**MB**	-0.004	-0.045	0.041	**MB**	-0.022	-0.015	-0.007
t-stat	*0.58*	*-4.62*	*3.82*	**t-stat**	*-0.36*	*-4.56*	*2.81*	**t-stat**	*-1.89*	*-1.41*	*-0.43*
Mom	0.021	-0.096	0.117	**Mom**	0.048	-0.135	0.182	**Mom**	-0.238	0.045	-0.283
t-stat	*0.38*	*-1.31*	*1.20*	**t-stat**	*0.90*	*-1.84*	*1.87*	**t-stat**	*-3.49*	*0.67*	*-2.80*
Rev	-0.032	-0.053	0.020	**Rev**	-0.035	-0.049	0.014	**Rev**	-0.047	-0.044	-0.003
t-stat	*-7.61*	*-12.36*	*4.99*	**t-stat**	*-8.04*	*-11.45*	*4.10*	**t-stat**	*-11.41*	*-9.67*	*-0.92*
Inv	-0.768	-1.048	0.281	**Inv**	-0.809	-0.922	0.113	**Inv**	-0.724	-1.025	0.301
t-stat	*-2.89*	*-3.62*	*0.92*	**t-stat**	*-3.32*	*-3.26*	*0.42*	**t-stat**	*-2.63*	*-3.83*	*1.10*
Prof	0.484	0.409	0.075	**Prof**	0.443	0.447	-0.003	**Prof**	0.357	0.574	-0.216
t-stat	*2.91*	*2.33*	*0.41*	**t-stat**	*2.67*	*2.61*	*-0.02*	**t-stat**	*2.36*	*3.40*	*-1.56*
Comp	-0.107	-0.758	0.651	**Comp**	-0.116	-0.599	0.483	**Comp**	-0.461	-0.122	-0.339
t-stat	*-1.12*	*-3.39*	*2.99*	**t-stat**	*-1.24*	*-2.95*	*2.39*	**t-stat**	*-3.15*	*-0.79*	*-1.71*

Panel B. Cross-Sectional Regressions in Segment Correlation and Credit Rating Groups

B1. Segment Correlation **B2. Credit Rating**

	Low	High	H-L		IG	Junk	NR	J-IG	J-NR	NR-IG
Beta	0.215	-0.042	0.257	**Beta**	0.121	0.092	0.137	-0.029	-0.045	0.016
t-stat	*1.76*	*-0.38*	*2.65*	**t-stat**	*0.71*	*0.55*	*1.29*	*-0.21*	*-0.39*	*0.13*
Size	0.000	0.000	0.000	**Size**	0.000	0.000	0.000	0.000	0.000	0.000
t-stat	*0.13*	*-0.80*	*0.63*	**t-stat**	*-0.52*	*0.92*	*-0.85*	*1.08*	*1.28*	*-0.64*
MB	-0.025	-0.034	0.008	**MB**	0.002	0.022	-0.029	0.020	0.051	-0.031
t-stat	*-1.19*	*-1.70*	*0.30*	**t-stat**	*0.13*	*1.31*	*-4.05*	*1.01*	*2.72*	*-2.13*
Mom	-0.049	0.161	-0.210	**Mom**	-0.248	0.330	-0.079	0.578	0.409	0.169
t-stat	*-0.38*	*1.14*	*-0.99*	**t-stat**	*-1.58*	*2.00*	*-1.35*	*2.72*	*2.10*	*1.01*
Rev	-0.048	-0.047	-0.002	**Rev**	-0.034	-0.006	-0.043	0.028	0.037	-0.008
t-stat	*-8.79*	*-8.51*	*-0.27*	**t-stat**	*-5.87*	*-1.04*	*-9.98*	*5.47*	*6.59*	*-1.54*
Inv	-0.856	-1.195	0.339	**Inv**	-0.603	-0.761	-0.859	-0.158	0.098	-0.256
t-stat	*-2.59*	*-3.01*	*0.73*	**t-stat**	*-1.64*	*-2.03*	*-3.06*	*-0.42*	*0.29*	*-0.69*
Prof	0.506	1.020	-0.514	**Prof**	0.365	0.559	0.389	0.194	0.169	0.025
t-stat	*1.99*	*4.70*	*-1.76*	**t-stat**	*2.12*	*1.56*	*2.26*	*0.60*	*0.48*	*0.12*
HiComp	-0.258	-0.121	-0.137	**Comp**	-0.145	0.360	-0.557	0.504	0.916	-0.412
t-stat	*-1.61*	*-1.71*	*-0.83*	**t-stat**	*-1.00*	*2.05*	*-3.48*	*2.36*	*3.98*	*-2.58*

Table 7A. Complexity Effects, Diversification Discount, and Skewness

Panels A and C present cross-sectional regressions of DGTW-adjusted returns on the Comp measure/HiComp dummy and controls, performed separately in each diversification discount/skewness group. Panel B adds the diversification discount (DDisc) measure to the regressions of DGTW-adjusted returns on high complexity dummies and controls (see Table 5 for definitions of the complexity variables). DGTW adjustment (described in detail in Data Appendix) adjusts returns for size, market-to-book, and momentum. DDis is the difference between conglomerate's market-to-book (defined, for this purpose only, as market cap over total assets) and the weighted average imputed market-to-book of its segments, where the weights are from segment assets, and imputed market-to-book is the average market-to-book of single-segment firms with the same two-digit SIC code as the segment. Skewness is total skewness of daily returns measured separately in each firm-year. DDisc/skewness groups split firms as above/below annual median of the DDisc/skewness measure. 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 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

A. Diversification Discount Groups

	Low	High	H-L
Beta	0.037	0.105	0.068
t-stat	*0.28*	*0.82*	*0.50*
Size	0.000	0.000	0.000
t-stat	*0.06*	*-0.61*	*-0.58*
MB	-0.031	-0.033	-0.002
t-stat	*-1.38*	*-1.17*	*-0.06*
Mom	-0.030	-0.062	-0.032
t-stat	*-0.19*	*-0.44*	*-0.15*
Rev	-0.052	-0.045	0.007
t-stat	*-5.31*	*-7.79*	*0.62*
Inv	-1.218	-0.372	0.846
t-stat	*-3.36*	*-0.83*	*1.47*
Prof	0.648	1.005	0.356
t-stat	*2.70*	*3.28*	*0.96*
HiComp	-0.051	-0.281	-0.230
t-stat	*-0.65*	*-3.08*	*-1.76*

B. Diversification Discount Control

	1	2	3
Beta	0.160	0.157	0.161
t-stat	*1.34*	*1.32*	*1.36*
Size	0.000	0.000	0.000
t-stat	*0.57*	*0.88*	*0.68*
MB	-0.041	-0.040	-0.045
t-stat	*-1.52*	*-1.49*	*-1.63*
Mom	-0.024	-0.033	-0.026
t-stat	*-0.22*	*-0.30*	*-0.24*
Rev	-0.048	-0.047	-0.048
t-stat	*-8.32*	*-8.28*	*-8.39*
Inv	-1.062	-1.027	-0.917
t-stat	*-2.95*	*-2.90*	*-2.41*
Prof	0.773	0.769	0.776
t-stat	*3.38*	*3.35*	*3.42*
DDisc	0.092	0.097	0.111
t-stat	*3.45*	*3.56*	*3.78*
HiComp	-0.108		
t-stat	*-1.78*		
HiSeg		-0.101	
t-stat		*-1.69*	
HiRSZ			-0.138
t-stat			*-2.03*

C. Return Skewness Groups

	Low	High	H-L
Beta	0.150	0.085	-0.065
t-stat	*1.45*	*0.91*	*-1.07*
Size	0.000	0.000	0.000
t-stat	*-1.57*	*-0.48*	*-0.03*
MB	-0.019	-0.033	-0.014
t-stat	*-1.96*	*-3.46*	*-1.04*
Mom	0.058	-0.097	-0.155
t-stat	*0.85*	*-1.71*	*-1.91*
Rev	-0.044	-0.044	0.000
t-stat	*-10.12*	*-10.92*	*-0.06*
Inv	-0.846	-0.966	-0.120
t-stat	*-3.26*	*-3.92*	*-0.56*
Prof	0.569	0.382	-0.187
t-stat	*3.62*	*2.36*	*-1.40*
Comp	-0.295	-0.351	-0.057
t-stat	*-2.46*	*-2.33*	*-0.38*

Table 8A. Complexity Effect and Credit Constraints

Panel A presents alphas of the zero-minus-high complexity portfolio that buys single-segment firms and shorts conglomerates with Comp measure above median for conglomerates. The alphas are from the five-factor Fama and French (2015) model, FF5, as well as FF5 augmented by one of financial constraints factors. Financial constraints factors are return spreads between the most and least financially constrained quintiles from sorts on the respective credit constraint measure: Kaplan and Zingales (1997) index (KZ), Whited and Wu (2006) index (WW), Hadlock and Pierce (2010) index (HP), credit rating (Cred), and expected default frequency, EDF. The rightmost three columns form KZ/WW/HP factors using only firms with R&D-to-sales ratio above median (HiR&D). Panel B presents betas of the zero-minus-high complexity portfolio with respect to the financial constraints factors from the same FF5 model augmented by one of financial constraints factors as in Panel A. 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 1986 to December 2016. The sample excludes stocks priced below $5 on the portfolio formation date.

Panel A. Alphas of Zero-Minus-High Portfolios

	α_{FF5}	α_{+KZ}	α_{+WW}	α_{+HP}	α_{+Cred}	α_{+EDF}	$\alpha^{HiR\&D}_{+KZ}$	$\alpha^{HiR\&D}_{+WW}$	$\alpha^{HiR\&D}_{+HP}$
Comp	0.354	0.270	0.358	0.345	0.339	0.329	0.391	0.359	0.378
t-stat	*4.01*	*3.35*	*4.06*	*3.98*	*3.44*	*3.91*	*4.40*	*4.12*	*4.32*
NSeg	0.353	0.257	0.328	0.352	0.322	0.320	0.365	0.353	0.372
t-stat	*3.93*	*3.23*	*3.67*	*3.91*	*3.17*	*3.75*	*3.95*	*4.05*	*4.12*
RSZ	0.488	0.362	0.442	0.430	0.362	0.433	0.485	0.455	0.472
t-stat	*3.40*	*2.61*	*2.99*	*2.90*	*2.70*	*3.01*	*3.12*	*3.11*	*3.19*

Panel B. Betas with respect to Financial Constraints Factors

	β_{KZ}	β_{WW}	β_{HP}	β_{Cred}	β_{EDF}	$\beta^{HiR\&D}_{KZ}$	$\beta^{HiR\&D}_{WW}$	$\beta^{HiR\&D}_{HP}$
Comp	-0.257	-0.016	-0.140	-0.056	0.065	-0.046	-0.096	-0.089
t-stat	*-5.50*	*-0.36*	*-2.29*	*-1.79*	*2.26*	*-1.85*	*-2.95*	*-3.46*
NSeg	-0.292	0.098	-0.003	-0.044	0.084	0.006	-0.115	-0.054
t-stat	*-6.27*	*2.27*	*-0.04*	*-1.68*	*2.87*	*0.21*	*-3.82*	*-2.31*
RSZ	-0.243	-0.002	-0.180	-0.100	0.031	-0.050	-0.051	-0.101
t-stat	*-3.66*	*-0.03*	*-1.55*	*-2.90*	*0.70*	*-1.23*	*-1.35*	*-2.71*

Table 9A. Complexity Effect and Sentiment

Panel A presents estimates from regressions that use sentiment index from Baker and Wurgler (2006) to predict returns to 1-HHI sorted portfolios named in the headings of the columns (see Table 3 in the paper for description of the portfolios). $Sent_{t-1}^{\perp}$ is the version of the sentiment index that is orthogonalized to business cycle variables by Baker and Wurgler. Panel B re-estimates predictive regressions from Panel A adding business cycle variables from Table 10 in the paper as additional controls.

Panel A. Univariate Regressions

	Zero	**Low**	**High**	**Z-H**	**Z-L**	**L-H**
Constant	0.784	0.715	0.802	-0.020	0.069	-0.088
t-stat	*3.60*	*3.32*	*3.74*	*-0.20*	*0.80*	*-1.19*
$\boldsymbol{Sent_{t-1}}$	-0.686	-0.506	-0.389	-0.296	-0.180	-0.117
t-stat	*-2.03*	*-2.07*	*-1.48*	*-1.47*	*-0.96*	*-1.29*
Constant	0.863	0.770	0.841	0.021	0.093	-0.071
t-stat	*3.83*	*3.46*	*3.74*	*0.21*	*1.05*	*-0.95*
$\boldsymbol{Sent_{t-1}^{\perp}}$	-0.901	-0.651	-0.484	-0.416	-0.250	-0.167
t-stat	*-2.41*	*-2.49*	*-1.71*	*-1.81*	*-1.14*	*-1.60*

Panel B. Macro Variables Controlled

	Zero	**Low**	**High**	**Z-H**	**Z-L**	**L-H**
Constant	-1.080	-1.065	-0.862	-0.217	-0.015	-0.190
t-stat	*-0.89*	*-1.00*	*-0.80*	*-0.36*	*-0.03*	*-0.43*
Sent(-1)	-0.732	-0.155	0.048	-0.780	-0.577	-0.201
$\boldsymbol{Sent_{t-1}}$	*-1.38*	*-0.39*	*0.11*	*-2.88*	*-1.95*	*-1.37*
Constant	-0.603	-0.856	-0.761	0.161	0.253	-0.081
t-stat	*-0.48*	*-0.80*	*-0.69*	*0.25*	*0.46*	*-0.18*
$\boldsymbol{Sent_{t-1}^{\perp}}$	-0.984	-0.351	-0.111	-0.873	-0.633	-0.240
t-stat	*-1.79*	*-0.89*	*-0.25*	*-3.06*	*-1.97*	*-1.46*