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Abstract*

We show that the post earnings announcement drift (PEAD) is stronger for conglomerates than single-segment firms. Conglomerates, on average, are larger than single segment firms, so it is unlikely that limits-to-arbitrage drive the difference in PEAD. Rather, we hypothesize that market participants find it more costly and difficult to understand firm-specific earnings information regarding conglomerates as they have more complicated business models than single-segment firms. This in turn slows information processing about them. In support of our hypothesis, we find that, compared to single-segment firms with similar size, conglomerates have relatively low institutional ownership and short interest, are covered by fewer analysts, these analysts have less industry expertise and also make larger forecast errors. Finally, we find that an increase in firm complexity leads to larger PEAD and document that more complicated conglomerates have greater PEADs. Our results are robust to a long list of alternative explanations of PEAD as well as alternative measures of firm complexity.

JEL Classifications: G11, G12, G14, G32, G33, M4, L14, D82

Keywords: innate business complexity, post-earnings-announcement drift, conglomerates, complicated firms.

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1. INTRODUCTION

In this paper, we examine the relation between innate business complexity (organizational form) and price formation by contrasting equity return reactions around earnings announcements for conglomerates and single-segment firms. We have two important findings: (i) conglomerates have larger post-earnings announcement drifts than single-segment firms that have the same level of surprise unexpected earnings, (ii) and this is attributable to the fact that conglomerates, by virtue of operating in multiple industries, have innately more difficult-to-understand business models which complicates information processing about them.

As suggested by Cohen and Lou (2012) there could be various distinct channels through which conglomerates' more complex business models could impede information processing about them. This may happen because investors may not possess a detailed understanding of how different business segments affect the total profits of a conglomerate. For example, investors may possess detailed knowledge of the weights of different business segments but may lack the ability to predict the impact of segment level sales on the value of the conglomerate. This may happen, for example, if some segments have high fixed costs while others have mostly variable costs. In such an instance, even if one knows the exact sales figures generated by each segment, it would be very difficult to predict the impact of the sales figures on profits without understanding the internal cost structure of the conglomerate. This in turn would complicate the analysis of conglomerates, slowing down the price discovery process about them and leading to under-reaction to earnings news.

In support of our predictions, first, we show that sophisticated market participants, including analysts, institutional investors and short-sellers, find it more difficult to understand conglomerates than single-segment firms. Specifically, we find that, once we control for size and other relevant firm-characteristics, conglomerates, compared to single-segment firms, have relatively low institutional ownership and short interest, are covered by fewer analysts, these analysts have less industry expertise and also make larger forecast errors. Unconditionally, conglomerates are much larger than single-segment firms and thus have more institutional ownership and analyst coverage. Controlling for determinants of institutional ownership and analyst coverage reveals though that institutions and analysts prefer not to deal with conglomerates if a similar single-segment firm is available, indicating that complex organizational structures impede information processing.

Second, using organizational structure as our proxy for innate business complexity, we find that firms with more complicated organizational structures (conglomerates) have larger post-earnings announcement drifts compared to simpler firms (single-segment firms). Specifically, we find that post-earnings announcement drift (PEAD) for an average conglomerate is at least twice as large as it is for an average single-segment firm. We attribute our findings to the fact that it is more costly and difficult to understand firm-specific earnings information regarding complicated firms and that information processing takes more time for complex firms, leading conglomerates to underreact to earnings surprises significantly more than single-segment firms.

Then, we investigate the reason for the larger PEADs for conglomerates. The larger drifts for conglomerates could be attributable to either (i) more news released per unit of unexpected surprise earnings (SUE) for conglomerates than single-segment firms or to (ii) under-reaction by investors to news about conglomerates. In an effort to distinguish the source of the difference in PEADs, we contrast the immediate as well as the delayed responses of single-segment firms and conglomerates for a hedge portfolio that is long the largest unexpected surprise earnings (SUE) decile and short the smallest SUE decile. Our analysis indicates that single-segment firms and conglomerates have similar hedge returns in the three days around earnings announcements. Coupled with stronger post-announcement drifts, this finding might imply more information is generated about conglomerates around earnings announcements compared to single-segment firms. Nevertheless, subsequent analysis reveals that our finding is not due to more information generation regarding conglomerates around earnings announcements but rather due to the fact that conglomerates under-react to earnings announcements when compared to single-segment firms. Following DellaVigna and Pollet (2009), we define delayed response ratio as the share of the total stock response to announcements that occurs with delay. We find that the delayed response ratio for conglomerates is 59.1%, which is 14.6% more than it is for single-segment firms' 44.5%. This result suggests that investors have more difficulty processing earnings related information regarding conglomerates and that information processing takes more time for complex firms, in line with our prediction.

Next, in an effort to understand if investors really have difficulty interpreting information related to more complicated firms we focus on periods during which innate business complexity increases. If the level of innate business complexity (conglomerate status) is related to a certain unknown variable X that also drives PEAD, then new conglomerates would likely have little exposure to this variable and one would expect new conglomerates to have low levels of PEAD.[1] Under our hypothesis, however, investors should have the greatest confusion when interpreting earnings announcements of new conglomerates, due to the significant and recent change to their complexity level. We find that an increase in innate business complexity, defined as a change in the conglomerate status, leads to higher PEAD. In particular, we find that PEAD for new conglomerates is double that of existing conglomerates and more than four times that of single-segment firms. Furthermore, we find that the stronger average PEAD for firms that have recently become conglomerates is attributable primarily to firms that have created a new line of business from within, without merging with another firm from a different industry.

Finally, we investigate whether the degree of innate business complexity matters in the cross-section of conglomerate PEAD returns. In doing so we utilize the dispersion in segment earnings growth rates, HTSD[2], as our proxy for conglomerate complexity. Hirshleifer and Teoh (2003) present a theoretical model which suggests that as long as some investors use a conglomerate's aggregate earnings growth rate, instead of individual segment growth rates, to extrapolate the future value of the firm, the firm will be mispriced. The model shows that higher dispersion in segment earnings growth rates with respect to the firm's aggregate growth rate will lead to higher information processing costs, which will lead to more mispricing for the firm. We find, consistent with this theoretical prediction, that conglomerates with high dispersion in their segments' growth rates have larger post-earnings-announcement drifts. This finding suggests that a higher degree of complexity among conglomerates leads to a higher level of PEAD and further supports the notion that higher innate business complexity reduces investors' ability to interpret publicly available but hard-to-process information.

[1] Imagine that a firm becomes a conglomerate if X exceeds a certain threshold. Then new conglomerates are likely to have X close to the threshold, while for old conglomerates it can become much higher than the threshold with time (assuming that old conglomerates disband if X drops below the threshold). X also has to be positively related to PEAD, because all single-segment firms (conglomerates) in this setup have X below (above) the threshold, and conglomerates, as we find, have stronger PEAD. Thus, new conglomerates will have lower X than old conglomerates and therefore lower PEAD.

[2] In order to calculate HTSD, first we compute the deviation of each segment's earnings growth rate from the firm's aggregate earnings growth rate and square it. Then, we value weight all segment deviation squared values by the amount of sales generated by that segment as a fraction of the total sales of the firm. Finally, we add up all the squared segment deviation values weighed by corresponding sales share values to calculate HTSD.

In all of our basic tests we control for the impact of the loss effect (Narayanamoorthy 2006), investor sophistication (Bartov, Radhakrishnan and Krinsky 2000), liquidity (Sadka 2006), analyst coverage (Gleason and Lee 2003)[3] as well as size and market-to-book. Our results are further robust to a long list of alternative explanations of PEAD such as potential spillover from the predictability documented in Cohen and Lou (2012), the impact of analyst responsiveness (Zhang 2008), the impact of ex-ante earnings volatility on earnings persistence (Cao and Narayanamoorthy 2012), the time-varying nature of earnings persistence (Chen 2013), as well as the impact of disclosure complexity (Miller 2010, You and Zhang 2009, Feldman, Govindaraj, Livnat, and Segal 2010, Lehavy, Li and Merkley 2011, Lee 2012).[4] Furthermore, we find no evidence that conglomerates are more likely to choose Fridays (DellaVigna and Pollet 2009) or days with more competing news (Hirshleifer, Lim and Teoh 2009) to announce their earnings.[5]

Our study contributes to two strands of literature. First, we add to the literature on the determinants of the post-earnings announcement drift (PEAD). We show that innate business complexity induces significant informational frictions that make it more difficult to understand earnings related information regarding complex firms. This in turn leads to larger PEAD. Specifically, we find that conglomerates have post-earnings announcement drifts that are at least twice as large as single-segment firms and that conglomerates' delayed response ratio is 14.6% higher than that of single-segment firms. Second, we complement the literature that studies the impact of organizational structure on information processing. Specifically, we document that, compared to single-segment firms with similar size and other firm characteristics, conglomerates have relatively low institutional ownership and short interest, are covered by fewer analysts, these analysts have less industry expertise and they also make larger forecast errors. Although past literature has documented the benefits of focus increasing conglomerate spin-offs, evidence is mixed about whether

[3] Gleason and Lee (2003) document that analysts play a significant role in mitigating market inefficiency. We use the number of analysts (*# Analysts*) as a proxy for this effect and control for both (*# Analysts*) and its interaction with SUE (*SUE* # Analysts*) in all of our main analyses to account for this. The exceptions are tables 6, 7 and 9 as using our usual complete set of controls would severely restrict the sample size.

[4] We investigate whether alternative explanations of PEAD, which could be tied to other dimensions of firm-complexity, can explain our results explicitly in Tables 8, 9 and 10.

[5] In unreported analyses we also find that our results are robust to controlling for the impact of limits-to-arbitrage measured via idiosyncratic volatility (Mendenhall 2004) as well as an alternative measure of investor sophistication measured via relative short interest. Results are available upon request.

conglomerates on average are harder to understand than single-segment firms. This is so, because there is evidence suggesting that those conglomerates which choose to break up are the ones that are subject to the most severe information dissemination problems (Krishnaswami and Subramaniam 1999). Since studying focus increasing spin-offs cannot inform us about the information environments of those conglomerates which choose not to break up, such studies suffer from a sample selection bias. We believe our analyses significantly improve our understanding of the different information environments faced by multi-segment and single-segment firms. These findings should be of interest to researchers, analysts and investors interested in the impact of innate business complexity on market efficiency.

The rest of the paper is organized as follows. Section 2 presents hypothesis development. Section 3 describes our measures of innate business complexity and other data utilized in this study and provides descriptive statistics. Section 4 provides our main results. Section 5 provides a comprehensive list of robustness tests. Section 6 concludes.

2. HYPOTHESIS DEVELOPMENT

Prior research has demonstrated the role that corporate focus can play in improving a firm's information environment. The literature has shown that focus-increasing spin-offs, equity carve-outs, and targeted stock offerings lead to a significant increase in coverage by analysts that specialize in subsidiary firms' industries as well as an improvement in analyst forecast accuracy for parent and subsidiary firms. Gilson, Healy, Noe, and Palepu (2001) attribute the improvement in analyst forecast accuracy following focus increasing spin-offs in part to increased disclosure, as all analysts gain access to disaggregated data for the parent and subsidiary firms after the breakup. Gilson et al. (2001) find that subsequent to firm spin-offs there is significant incremental improvement in forecast accuracy for specialist analysts relative to non-specialists[6] suggesting that focus-increasing restructurings may reduce analysts' task complexity (Clement 1999) and may also lead to better facilitation of information transfers by analysts with industry expertise (Hilary and Shen 2013). In a related paper, Chemmanur and Liu (2011) theoretically show that focus-increasing restructurings should lead to higher information production by institutional investors. They attribute the increase in

[6] An analyst covering a firm is considered a specialist if he/she is also currently covering several firms in the same industry (industry affiliation of a conglomerate is determined by the industry affiliation of its larger segment).

information production to two reasons. First, division of consolidated firms into less complex units with their own financial reports reduces outside investors' information production costs. Second, focus-increasing restructurings allow institutional investors to concentrate their investment in those parts of the conglomerate about which they have expertise.

In a concurrent and relevant paper to Gilson et al. (2001), Krishnaswami and Subramaniam (1999) suggest that conglomerates that choose to break-up are those that are subject to the most severe information dissemination problems. Krishnaswami and Subramaniam (1999) report that the average forecast error of a conglomerate that breaks up is four times that of a similar conglomerate that doesn't break up. While it is clear that focus increasing spin-offs lead to better information dissemination for those conglomerates that choose to break-up, this is by no means a clear indication that single-segment firms on average are easier to analyze than multi-segment firms in the full cross-section of stocks. Thus, we believe it is important to investigate if it is indeed more difficult to understand conglomerates than single-segment firms by directly comparing their information environments. Such a direct comparison of the information environments of conglomerates and single-segment firms, however trivial it may seem, has rarely been conducted in the past literature. To the best of our knowledge, the only paper that studies the impact of conglomeration on analyst forecast errors in the full cross-section is by Thomas (JFE 2002). Thomas (2002) measures firm complexity as the sum of squared shares of segment assets where segment asset shares are calculated by scaling segment asset values by the firm's total asset value (we use sales instead of assets in a similar measure). He finds over the 1986 to 1995 time period that the sign of the relation between forecast errors and firm complexity varies depending on the controls he uses. Given the inconclusive findings in Thomas (2002) as well as the sample selection biases suffered by the literature that studies conglomerate spin-offs, it is fundamentally an empirical question whether analyst forecast errors are larger for conglomerates or single segment firms in the larger cross-section, over a longer timer-series.

In a seminal paper, Cohen and Lou (2012) find that conglomerates take longer to incorporate industry-wide shocks into their prices compared to single-segment firms. In particular, Cohen and Lou (2012) find that returns to pseudo-conglomerates, made up of single-segment firms, predict the returns to actual conglomerates one month ahead, which indicates that conglomerates take an extra month to incorporate industrywide shocks into their prices.[7] Our paper builds on the arguments used by Cohen and Lou (2012) and expands on their analyses by investigating how investors process a large chunk of information about the complicated firm itself (earnings announcement), instead of looking at how they process the information about the industries the complicated firm operates in as in Cohen and Lou (2012). The challenges faced by the investors in our setup, i.e., disaggregating the earnings announcement into information about different segments, are different from the challenges investors face in the Cohen and Lou analysis, i.e., aggregating industry-level news about segments to revise the valuation of the conglomerate. Nevertheless, we propose that the channels through which innate business complexity impedes information processing about the firm are similar to the channels suggested in Cohen and Lou (2012).

Our first hypothesis suggests that an average conglomerate is more difficult to understand for investors than an average single segment firm because its business model is more complicated. More specifically investors could face difficulty determining the impact of segments with differing business characteristics and gross margins on the net profits of the conglomerate. Hence, we predict that, in the absence of detailed segment level information such as knowledge about gross margins, it will be significantly more difficult to interpret conglomerates' earnings news compared to single-segment firms. Thus, we hypothesize that conglomerates' innate business complexity impedes information processing about them and that this in turn reduces the willingness of sophisticated investors to invest or trade in multi-segment firms, ultimately slowing down the price discovery process for multi-segment companies. In particular, the first hypothesis states that, all else equal, conglomerates are expected to have lower institutional ownership, lower short interest, lower turnover, less analyst coverage, and higher analyst forecast errors.

Our second hypothesis builds directly on our first one and states that firms with greater innate business complexity (conglomerates) should have larger PEADs compared to simpler firms (single-segment firms) due to the slower and more difficult price discovery process. It takes longer to impound the performance of distinct business units into the price of a conglomerate than it takes to reflect the effect of earnings related news in the price of a single-segment firm. Consequently, we

[7] Pseudo-conglomerate return replaces real segments of a conglomerate by average returns to all single-segment firms in their industry and then takes the weighted average of these industry returns using the weights of the real segments in the conglomerate.

expect an under-reaction to earnings related news for conglomerates compared to single segment firms, followed by a larger drift.

Our third hypothesis implies that the larger PEADs observed for conglomerates are not attributable to conglomerates releasing more news per unit of SUE but rather due to a genuine difficulty of processing firm-specific earnings information regarding conglomerates. We test the validity of the third hypothesis by contrasting the immediate return reactions and delayed response ratios for single-segment firms and conglomerates for a hedge strategy that goes long in the largest SUE decile and short in the smallest SUE decile.

Our fourth hypothesis formulates that the degree of complexity affects the magnitude of PEAD. We support our fourth hypothesis by showing that an increase in firm complexity leads to higher PEAD and by documenting that more complicated conglomerates have larger PEADs than less complicated conglomerates.

To the best of our knowledge, there is no empirical research on the relation between innate business complexity (organizational structure) and the post-earnings announcement drift (PEAD) anomaly. The literature on PEAD largely focuses on how capital market characteristics such as information production by the firm, information uncertainty and the information processing of investors can offer an understanding of the post-earnings announcement drift. Although firm complexity could be measured by one or more of the above proxies, these proxies could also be affected by factors other than innate business complexity such as managers' actions to distort information. The number of segments (conglomerate status) which is an input-based measure, as opposed to output based measures like noisy earnings and return volatility, can thus help us to better identify innate business complexity.[8] Furthermore, as multi-segment firms, on average, tend to be larger, more liquid, less volatile, and more transparent, if information processing about them is indeed more complicated, then the economist should attribute this to the complexity of their operations and not to alternative explanations such as information uncertainty. Finally, using conglomeration as our proxy for innate business complexity should allow us to include a more extensive array of control variables in our analyses reducing endogeneity concerns.

[8] We thank an anonymous referee for helping us in elaborating the distinctness of innate business complexity.

In an attempt to establish the uniqueness of our results we need to control for alternative explanations for PEAD. In a recent paper Cao and Narayanamoorthy (2012) document that post-earnings announcement drift (PEAD) is a function of both the magnitude of an earnings surprise (SUE) and its persistence. Cao and Narayanamoorthy (2012) show that, contrary to the expectations of the market, firms with higher (lower) ex-ante earnings volatility have lower (higher) earnings surprise (SUE) persistence and document that PEAD returns due to earnings volatility are concentrated in firms with the smallest trading frictions, i.e. those firms that have the lowest ex-ante earnings volatility. Since conglomerates, on average, have smaller trading frictions than single-segment firms we control for the impact of ex-ante earnings volatility (EarnVol) on PEAD and document that our results are virtually unchanged and as such are distinct from the impact of ex-ante earnings volatility on PEAD studied in Cao and Narayanamoorthy (2012).

In another paper that investigates the impact of information complexity on PEAD, Chen (2013) documents that investors have difficulty understanding the time-varying nature of earnings persistence and their failure to incorporate this characteristic into the accounting and economic fundamentals leads to the post-earnings announcement drift. If there is a systematic difference in the time-varying nature of earnings persistence between single-segment firms and conglomerates, then such a difference could explain our findings. We find that controlling for the impact of time-varying earnings persistence (EP) documented in Chen (2013) slightly reduces the coefficient on the interaction of SUE with the conglomerate dummy but our main results are largely unchanged suggesting that the impact of innate business complexity, measured via organizational structure, on PEAD is distinct from the impact of time-varying earnings persistence on PEAD.

Next, we investigate whether varying analyst responsiveness for conglomerates and single-segment firms could explain our results. Following Zhang (2008), we construct a measure of analyst responsiveness (DRESP) and investigate whether its interaction with SUE could reduce the economic and statistical impact of business complexity on PEAD. Our results suggest that the impact of DRESP on PEAD cannot explain our main findings, either.

Then, we test if the impact of innate business complexity (conglomerate status) on PEAD could be explained by informational frictions associated with disclosure complexity. In a relevant study, Lee (2012) finds that, for the same level of earnings surprise, investors first underreact and then respond in the direction of the surprise with a delay to 10-Q filings if a given 10-Q is textually more complicated. Since 10-Q's are filed at a date later than the actual earnings announcements, Lee (2012) is not a direct investigation of the impact of disclosure complexity on PEAD. Following Li (2008) we construct the Gunning FOG index as our proxy for disclosure complexity, and analyze its direct impact on PEAD. To our surprise, we find that the interaction of surprise unexpected earnings (SUE) with firm-level textual complexity (FOG) predicts PEAD with a negative sign when we control for the impact of organizational structure on PEAD. This result would suggest that our results are not affected by the impact of disclosure complexity.

Finally, we contend that the effect we study is distinctly different from results in Cohen and Lou (2012) who investigate how industry-wide news is incorporated into the prices of single-segment firms and conglomerates. To distinguish the impact of innate business complexity on returns attributable to firm-specific news, from the impact of innate business complexity on returns attributable to industry-wide news, we specifically control for potential spillover from the predictability documented in Cohen and Lou (2012). Our results suggest that larger PEADs for conglomerates are distinct from the predictability documented in Cohen and Lou (2012).

3. DATA

We use three measures of innate business complexity. The first measure, Conglo, is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. The firm is deemed to be a conglomerate if it has business divisions in two or more different industries, according to Compustat segment files. Industries are defined using two-digit SIC codes. The second measure of complexity, NSeg, is the number of divisions with different two-digit SIC codes. The third measure, Complexity, is a continuous variable based on sales concentration. Complexity equals 1-HHI, where HHI is the sum of sales shares of each division squared, HHI= $\sum_{i=1}^{N} s_i^2$, where sales share, s_i, for each division is the fraction of total sales generated by that division. According to the third definition of complexity, a firm with sales in a single segment would have an HHI of 1 and a Complexity measure of 0, whereas a firm with sales in a large number of industries could achieve a Complexity score close to 1.

Our measure of PEAD is the slope from the Fama-MacBeth (1973) regression of cumulative post-announcement returns on earnings surprises. Post-announcement cumulative abnormal returns (CARs) are cumulated between trading day 2 and trading day 60 after the earnings announcement. CARs are size and book-to-market adjusted following Daniel et al. (1997) (also known as DGTW).

Earnings announcement dates are from COMPUSTAT, and daily returns are from CRSP daily files. We measure earnings surprise as standardized unexpected earnings (SUE), defined as the difference between earnings per share in the current quarter and earnings per share in the same quarter of the previous year, scaled by the share price for the current quarter.[9] Since we calculate SUE and PEAD values as in Livnat and Mendenhall (2004) we use the same sample selection criteria. In doing so, we restrict the sample to firm-quarter observations with price per share greater than $1 as of the end of quarter t in an effort to reduce noise caused by small SUE deflators. We also keep only those observations with non-negative book value of equity at the end of quarter t-1, while excluding those observations with market value of equity less than $5 million at the end of quarter t-1.

Our sample period is determined by the availability of the segment data and lasts from January 1977 to December 2010. All other variables are defined in the Data Appendix.

3.1 Descriptive Statistics, Organizational Structure and Limits to Arbitrage

Complex firms tend to be larger, more liquid, less volatile, and more transparent and as such they are expected to have lower limits to arbitrage. In this section, we empirically verify the relationship between firm complexity and the traditional measures of limits to arbitrage.

Panel A of Table 1 reports the full distribution of SUE, Complexity=1-HHI, and the number of segments for all firms and for conglomerates only. A few numbers are particularly noteworthy. First, it is important to note that SUE changes by 0.139 (0.064 minus -0.075) between the 95th and the 5th percentiles and by 0.274 (0.129 minus -0.145) between the 97.5th and the 2.5th SUE percentiles – this information will be used later to evaluate the economic magnitude of the SUE slope in the Fama-MacBeth regressions of post-announcement CAR on SUE. Second, we notice that most firms in our sample are not conglomerates (the median number of segments in the full sample is 1) and most conglomerates have two segments (the median number of segments for conglomerates is 2 except for a few years early in the sample).[10] A relatively large number of conglomerates report three segments and some have four segments, whereas conglomerates with five or more segments make up less than

[9] In unreported tables, calculating SUE as the deviation from consensus analyst forecasts, we find results that are qualitatively and quantitatively consistent with our main findings. Results are available upon request.

[10] In untabulated results, we find that 27% of firms in the sample are conglomerates. This number varies from 47% in the late 1970s to 17% in the late 1990s back to 25% in the 2000s.

2.5% of the full sample (and thus less than 10% of all conglomerates). Third, the distribution of innate business complexity suggests that there is a significant number of low-complexity firms. For example, a two-segment firm, for which one of the segments accounts for 95% of the revenues, would have a complexity measure of 0.095. This level of complexity is comparable to the 10th complexity percentile among conglomerates, which is only 0.079. A two-segment firm, for which one of the segments accounts for 90% of sales, has a complexity measure of 0.18. This level of complexity is comparable to the 25th complexity percentile among conglomerates. These observations suggest that even small segments are reported in Compustat Segment files and that we are not lumping together single-segment firms with conglomerates that have many small unreported segments. [11]

The rest of Table 1 compares the firm characteristics of single-segment firms and multi-segment firms (conglomerates). In Panel B, we summarize earnings surprises (SUE) and announcement returns (CAR(-1;1)) for the two types of firms specified as above. CAR(-1;1) is size and book-to-market adjusted as in DGTW. Panel B1 reports the mean CAR values, in an attempt to assess whether conglomerates, on average, have more positive earnings surprises, and Panel B2 reports the means of absolute values of CAR(-1;1), testing whether earnings surprises experienced by conglomerates are different in magnitude.

We find in Panel B1 that SUEs of the two firm groups (single-segment and multi segment) are, on average, positive at 0.156% and 0.155% of the stock price, respectively, and that conglomerates have somewhat more positive CARs, but the difference is never statistically significant.

Panel B2 shows that the magnitude of the announcement CARs is significantly smaller for conglomerates than it is for single-segment firms, whereas the average absolute magnitude of SUE is similar for both groups of firms. While the first result is not surprising, since conglomerates are significantly larger and thus less volatile than single-segment firms, the second one (similar SUE magnitude despite different size) offers a preview of our findings in the next section that conglomerates have poor analyst coverage compared to single-segment firms of the same size. The smaller absolute CARs of conglomerates, coupled with similar SUE of conglomerates and single-

[11] The number of firms in quarterly Compustat files is larger than the number of firms reported in Compustat segment files, because single-segment firms and firms with relatively small segments do not have to report segment data. In our main analysis, we do not use firms covered by Compustat quarterly, but rather those covered by Compustat segment files, because we cannot exclude the possibility that such firms have small unreported segments. However, we confirm that our main results remain qualitatively intact if we assume that all firms that are on Compustat quarterly, but not on Compustat segment files are single-segment firms.

segment firms, are also suggestive that the stronger PEAD for conglomerates is unlikely to imply that conglomerates experience more information revelation at earnings announcements.

Panel C summarizes the median values of several liquidity measures for single-segment firms, and multi-segment firms. The first three - the Gibbs measure (Hasbrouck, 2009), the Roll (1984) measure, and the effective spread estimate of Corwin and Schultz (2012) estimate the effective bid-ask spread. We find that the bid-ask spread of a representative conglomerate is roughly one-third to two-thirds lower than the bid-ask spread of a representative single-segment firm. The fourth liquidity measure, the Amihud (2002) measure, estimates the price impact and shows that conglomerates experience 50% less price impact when compared to a representative single-segment firm. The last measure is a catch-all trading cost measure from Lesmond et al. (1999). This measure calculates the fraction of zero-return days in each firm-year and assumes that stocks are not traded when the trading costs are higher than the expected profit from trading. Thus, a greater fraction of zero-return days is synonymous with higher trading costs. We find that for conglomerates the median number of zero-return days is 11.8%, as opposed to 14.1% for single-segment firms and that the difference is statistically significant.

In summary, all liquidity measures in Panel C strongly suggest that conglomerates are significantly more liquid than single-segment firms. Thus, the liquidity measures suggest that if the link between PEAD and complexity were driven by liquidity effects, then PEAD would be stronger for single-segment firms, contrary to our hypothesis. This observation also suggests that, controlling for the interaction between PEAD and liquidity would make the relation between PEAD and complexity economically even more significant.

4. RESULTS

4.1 Information Production for Conglomerates and similar Single-segment firms

Our analysis in Table 1 suggests that conglomerates have lower limits to arbitrage. Nevertheless, building on our first hypothesis that conglomerates have greater innate business complexity and as such are more difficult to understand, we predict that analysts will be discouraged from following conglomerates while sophisticated investors will be less likely to invest and trade in them. As a result we predict that there will be less information production about multi-segment firms compared to single-segment firms.

In Table 2, we analyze the link between innate business complexity and information production about the firm by comparing single-segment firms and conglomerates across several dimensions. We specifically investigate the impact of innate business complexity on the information production by equity analysts, institutional investors and short sellers. Furthermore, we also investigate the differences in accounting disclosure quality of conglomerates and single-segment firms using segment disclosure quality as in Franco, Urcan, and Vasvari (2015). Institutional ownership (relative short interest) is the number of shares held by institutions (number of shares shorted) divided by number of shares outstanding. For analyst coverage, in addition to utilizing the traditional measure of analyst coverage, the number of analysts following the firm, we also measure the quality of the coverage by analyzing the number and fraction of specialists following the firm. An analyst following a firm is categorized as a specialist in that quarter, if the analyst covers five or more firms in the same industry in a given quarter (we use both two-digit and three-digit SIC codes to define an industry). For a conglomerate, specialists are defined using the industry affiliation of its main segment.

Size potentially has a large confounding effect on the link between firm complexity and information production about the firm. Larger firms are known to attract more attention of analysts and institutions, and conglomerates are roughly twice as large as single-segment firms are. While conglomerates are harder to understand due to their business complexity, the benefits of understanding conglomerates can be greater due to their larger size. Thus, in order to assess how business complexity impacts information production, we have to control for size by comparing conglomerates to single-segment firms of similar size.

In Panel A of Table 2[12], we distribute conglomerates and single-segment firms into size deciles formed using CRSP breakpoints. While this method of controlling for size is imperfect, it turns out powerful enough to elicit that conglomerates have less analyst coverage and their coverage is of lower quality than that of single-segment firms. In all size deciles, conglomerates are followed by fewer analysts and fewer specialists. We also observe that a smaller percentage of analysts covering conglomerates are specialists. The biggest difference is in the number of specialists, as single-

[12] We test for the statistical significance of the difference between single segment firms and conglomerates separately in each size decile for all variables analyzed in Table 2. Differences for all analyst coverage variables, forecast error, segment disclosure quality, turnover and relative short ratio are almost universally statistically significant at the one percent level in all size deciles. The differences in institutional ownership between conglomerates and single-segment firms are almost universally not statistically significant across size deciles. The differences in forecast dispersion are statistically significant in the larger size deciles.

segment firms have 25% to 40% higher percentage of specialists. Both the relative and absolute differences in analyst coverage peak in size deciles six to eight, suggesting that conglomerates which suffer from relatively low quality coverage are relatively large firms and are not obscure micro-cap multi-segment firms.

Once we control for size we also find that conglomerates suffer from larger analyst forecast errors due to the lower quality and the quantity of analyst coverage they receive. As the seventh row of Panel A suggests, conglomerates have larger analyst forecast errors in all size deciles but one (decile two), and the difference is material: on average, conglomerates have 15% larger forecast errors compared to single-segment firms controlling for size. Once again, the difference is mainly observed in the deciles with the largest conglomerate population: the differences in forecast errors are particularly large, in relative terms, in size deciles seven, nine and ten. Not only do we find the forecast errors to be larger for conglomerates compared to single-segment firms of similar size, but we also find the forecast dispersion / analyst disagreement regarding conglomerates is also larger (except for the two smallest size deciles).

Further supporting our hypothesis, we find that institutional investors and short sellers also find processing information about conglomerates harder. Before controlling for size (see Panel B1), conglomerates have significantly more institutional ownership compared to single-segment firms. Sorting firms into size-deciles, however, leads to a significantly different conclusion. We find that while in size-deciles five, six and seven conglomerates have more institutional ownership, the opposite is true in size deciles eight, nine and ten. We observe similar patterns regarding share turnover and relative short interest, as the difference in short interest (turnover) between single-segment firms and conglomerates increases with firm size, suggesting that institutions, short sellers, and stock traders in general tend to avoid conglomerates if single-segment firms of comparable size are available. Taken together, our analyses suggest that there is less information production about conglomerates compared to single-segment firms of similar size and that the relative difficulty of information processing is especially higher for larger conglomerates.

In Panel B2, we control for size in a different way: we match each conglomerate to a single-segment firm with the closest market cap. We observe again, consistent with Panel A, that conglomerates are followed by 1-2 analysts and specialists less than single-segment firms of comparable size, which constitutes a difference of 20-30% in the quality of analyst coverage. In terms of fraction of specialists, we find, for example, that on average 70% of analysts covering a single-segment firm specialize in its three-digit SIC industry, but only 57% of analysts covering a conglomerate specialize in the three-digit SIC industry of its main segment. All differences in analyst coverage are highly statistically significant and are observed in the vast majority of quarters.

As a consequence of lower quality analyst coverage, Panel B2 also reports that analyst forecast error is 18% higher for conglomerates than it is for single-segment firms of the same size, and the difference is significant with a t-statistic of 3.29. A similar result is observed for analyst forecast dispersion as forecast dispersion is 33% higher for conglomerates than it is for single-segment firms of the same size (.24 vs .18), and the difference is significant with a t-statistic of 3.24.

We find similar patterns for institutional ownership, relative short interest[13] and turnover. While before size-matching the average conglomerate has 3.8% more institutional ownership, after size-matching, the level of institutional holding is indistinguishable between conglomerates and single segment firms. Similarly, the difference in the relative short interest (RSI) in single-segment firms and conglomerates also increases after size-matching. Before-size matching average RSI for conglomerates is 2.2%, while it is 2.5% for single-segment firms for a 0.3% difference in favor of single-segment firms. After size-matching this difference becomes even more severe and increases to 0.5%. A very similar pattern is observed for turnover, as before-size matching it is 0.6% higher in favor of single-segment firms, but size-matching increases this difference to 1.4%.

Significant differences between Panels B1 and B2 illustrate the importance of controlling for size when comparing conglomerates and single-segment firms for variables related to information production. If we do not match by size, we find that information production about conglomerates, due to their larger market cap, is greater at least according to some measures. Panel B1 suggests that conglomerates have lower limits to arbitrage, and thus the stronger PEAD for conglomerates is unlikely to pick up the well-known relation between PEAD and limits to arbitrage (Bartov et al., 2000, Mendenhall, 2004, etc). Panel B2 looks at a particular wrinkle that is central to our story,

[13] Short interest can also reflect a directional bet, but this consideration works against us finding that short sellers avoid conglomerates, like institutions and analysts do. A long literature on the conglomerate discount, starting with Lang and Stulz (1994) and Berger and Ofek (1995), finds that conglomeration is, on average, value-destroying, and leads to conglomerates having worse operating performance and lower price multiples. Barinov (2018) further shows that conglomerates, on average, underperform by 3-6% per annum on a risk-adjusted basis. Hence, conglomerates should be attractive shorting targets everything else fixed, and the fact that we find the opposite result is a strong indication that innate business complexity matters.

information production, and finds that the conglomerate status implies, all else equal, less attention from analysts and sophisticated investors.

In Panel C, we run panel regressions that include more controls beyond just size as in Panel B, to better illustrate the role organizational structure plays on analyst coverage, institutional ownership, turnover and relative short interest.[14] In doing so, in addition to firm size, we control for market-to-book, CAPM-beta, lagged returns, momentum returns, share price, capital structure, firm-age and other firm-characteristics deemed relevant by the existing literature where necessary.[15] Most importantly in all of our regressions we account for the impact of geographic complexity on the firm's information environment. Geographic complexity, (GeoMulti), is a dummy variable equal to one if the firm generates its sales from a multitude of geographic segments and zero if the firm generates all of its sales from the same geographic segment. It is important to understand the differential impact of geographic complexity and control for its impact on PEAD, as some previous studies suggest it as a proxy for business complexity.[16] Our analyses reveal that while operating in multiple business segments leads to a deterioration of the information environment of the firm, the same cannot be said for firms that operate in multiple geographies. While the coefficient on the conglomerate dummy is negative in columns (1), (3), (4) and (5), indicating that conglomerates have lower analyst coverage, institutional ownership, turnover and relative short interest, the coefficient on GeoMulti, our proxy for geographic complexity, is positive in these four columns. Furthermore, we find a positive and statistically significant coefficient on Conglo in column (2), whereas the coefficient on GeoMulti is statistically insignificant, suggesting that innate business complexity leads to larger analyst forecast errors but geographic complexity has no effect on forecast accuracy. Taken together, these results suggest that while organizational complexity (innate business complexity) has an adverse effect on the information environment of the firm, the same is not true for the impact of geographic complexity.

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[14] For the panel regressions we run Panel C of Table 2 we cluster standard errors by firm-year, following Peterson (2009).

[15] The turnover regression uses the control variables from Chordia et al. (2007), the institutional ownership regression follows Gompers and Metrick (2001), and the short interest regression follows Barinov and Wu (2014).

[16] For example, Duru and Reeb (2002) study the impact of international diversification on analyst accuracy and report that prior to year 2000 analyst forecast accuracy is lower for firms with internationally more diverse operations. In unreported results we replicate and extend Duru and Reeb (2002) and find no evidence that international diversification reduces analyst forecast accuracy in the post-2000 period. Furthermore, we find that innate business complexity, measured using conglomerate status, is associated with lower analyst accuracy, in line with our main hypothesis.

In summary, in Table 2, we find that while a representative conglomerate is covered by somewhat larger number of analysts than a representative single-segment firm due to the conglomerate being much larger, this extra coverage is of poor quality, since it comes primarily from non-specialists and probably even dilutes the average analyst quality. Controlling for the confounding effect of size makes the negative relation between firm complexity and the quality of analyst coverage really stand out: when compared to single-segment firms of similar size, conglomerates are followed by a fewer number of analysts and specialists, and those analysts make larger forecast errors. Lower information quality production about conglomerates compared to single-segment firms of similar size is not confined to analysts. We also find that institutional investors and short-sellers face similar difficulty understanding conglomerates and thus refrain from investing or trading in them. We conclude that the complex nature of operating in multiple lines of business makes conglomerates significantly more difficult to understand in the eyes of market participants including equity analysts, institutional investors and short sellers. Next, we investigate how the market reacts to firm-specific information about conglomerates and single-segment firms.

4.2 Main Result: Business Complexity leads to higher Post Earnings Announcement Drift

Table 3 presents our main results, as we study the relation between PEAD and innate business complexity. We perform Fama-MacBeth (1973) regressions with post-announcement cumulative abnormal returns (CAR(2;60))[17] on the left-hand side and earnings surprise (SUE) and its interaction with alternative measures of innate business complexity on the right-hand side:

$$CAR_{2;60} = \gamma_0 + \gamma_1 \cdot SUE_0 + \gamma_2 \cdot Complexity_0 + \gamma_3 \cdot SUE_0 \cdot Complexity_0$$

Our measure of PEAD is the (positive) slope on SUE. Higher values of complexity measures utilized in this study correspond to a higher degree of complexity by construction. In this context observing a stronger PEAD for complex firms is associated with finding a positive coefficient on the interaction of SUE and innate business complexity.[18]

[17] We use size and book-to-market adjusted abnormal returns as in DGTW.

[18] We contrast single segment firms' and conglomerates' PEAD returns for comparable levels of earnings surprises in an effort to understand whether investors take longer to process the same amount of information when they are confronted with more complex firms. A positive loading on the interaction of innate business complexity with SUE, however, would also imply a tradable strategy as described in Fama (1976), who shows in Chapter 9 that slopes from Fama-MacBeth regressions are returns to tradable portfolios. In Table 5 and columns 7-9 of Table 10, we further study and document the tradability of this strategy using portfolios.

The literature on price momentum (see, e.g., Lee and Swaminathan, 2000, Lesmond et al., 2004, Zhang, 2006, and others) finds a puzzling absence of momentum for microcaps (stocks in the lowest NYSE/AMEX market cap quintile). Consequently, all results that momentum is stronger for firms with higher limits to arbitrage hold only in the sample with microcaps excluded. Since PEAD and price momentum are two related anomalies, we choose to exclude microcaps from our analysis as well. Another benefit of excluding microcaps is that microcaps are dominated by single-segment firms, and our regression analysis that compares PEAD for single-segment firms and conglomerates would have virtually no basis for such a comparison among microcaps.

The first column in Table 3 estimates PEAD in the pairwise regression of CAR(2;60) on SUE. The regression estimates that the difference in SUE between the 97.5th and 2.5th (95th and the 5th) SUE percentiles implies a CAR of 2.79% (1.42%) in the three months following the announcement.

In the second column, we perform the first test of our main hypothesis by regressing CARs on SUE, the conglomerate dummy, and the interaction of SUE and the conglomerate dummy. The interaction of the conglomerate dummy and SUE is highly significant and suggests that for conglomerates PEAD is 3.86% (1.96%) greater per three months than it is for single-segment firms when we estimate the difference in the PEADs by using the SUE differential between the 97.5th and the 2.5th (95th and 5th) SUE percentiles.

The third column estimates the relation between PEAD and conglomerate status controlling for the effects of market-to-book (MB), size (Size), institutional ownership (IO), loss effect (Loss), liquidity (Amihud), analyst coverage (# Analysts) and the interactions of this large set of controls with SUE. The third column verifies some of the previous findings in the literature as the interaction of SUE with Amihud is positive and statistically significant (verifying the relationship between illiquidity and PEAD), while the interactions of SUE with the number of analysts and the loss dummy are negative and statistically significant (verifying the impact of the loss effect as well as the impact of analyst coverage on PEAD). We find that controlling for the interactions of SUE with additional firm characteristics that may impact PEAD slightly reduces the loading on the interaction term between SUE and the conglomerate dummy from 0.141 to 0.129.

Columns (4) and (5) repeat the analyses conducted in columns (2) and (3), and replace the conglomerate dummy with the continuous complexity measure Comp, 1-HHI. The results in columns (4) and (5) are qualitatively similar to the results in columns (2) and (3): more complex firms have significantly stronger PEAD for the same level of SUE, and this relation persists when we control for market-to-book (MB), size (Size), institutional ownership (IO), loss effect (Loss), liquidity (Amihud), analyst coverage (# Analysts) and the interaction of these of controls with SUE. The magnitude of the coefficient on the product of SUE and the complexity measure, Comp, suggests that PEAD for conglomerates is more than twice as large as the PEAD for single segment firms: the mean level of the complexity variable for conglomerates is 0.368[19], thus the slope of 0.313 in column (4) would estimate the difference in PEADs of a representative single-segment firm and a representative conglomerate at 3.15% (1.60%) when the SUE differential between the 97.5th and the 2.5th (95th and 5th) percentiles is used in the estimation.

Columns (6) and (7) use the number of segments (with different two-digit SIC codes) as a proxy for complexity. Once again, the interaction term between SUE and complexity, NSeg, is statistically significant and the economic significance of the interaction term is little changed after controlling for market-to-book (MB), size (Size), institutional ownership (IO), loss effect (Loss), liquidity (Amihud), analyst coverage (# Analysts) and the interaction of these of controls with SUE. The magnitude of the coefficient on the product of SUE and the number of segments, NSeg, suggests that PEAD for conglomerates is roughly twice as large as the PEAD for single segment firms: as the median conglomerate has 2.2 segments the slope of 0.069 on SUE*NSeg in column (6) would estimate the difference in PEADs of a representative single-segment firm and a representative conglomerate at 2.27% (1.14%) when the SUE differential between the 97.5th and the 2.5th (95th and 5th) percentiles is used in the estimation.[20]

4.3 Joint Impact of Innate Business Complexity and Investor Sophistication on PEAD

Since Bartov et al. (2000), it has been well documented that sophisticated investors' trading can help reduce the level of the post-earnings announcement drift anomaly. Bartov et al. (2000) attribute this to unsophisticated investors' misperception about the process which underlies earnings to be a seasonal random walk. They suggest and document that sophisticated investors such as institutions understand the pricing implications of earnings surprises better and hence propose and empirically

[19] Complexity of 0.368, or HHI equal to 0.632, roughly corresponds to a two-segment firm with one segment taking slightly over 76% of sales, or to a three-segment firm with one segment taking 78% of sales and the other two taking 12% and 10% respectively.

[20] Results in column (6) of Table 3 would estimate the PEAD return to a representative conglomerate at 4.16% (2.09%) vs. 1.89% (0.95%) for a single segment firm when the SUE differential between the 97.5th and the 2.5th (95th and 5th) percentiles is used in the estimation.

verify that there should be less mispricing and lower PEADs in stocks largely held by sophisticated investors.

In Panel B.2 of Table 2 we show that, controlling for size, single-segment firms and conglomerates have similar levels of institutional ownership on average. This would suggest, ex-ante, that there is no reason for investor sophistication to impact PEAD differently for single-segment and multi-segment firms. Furthermore, we control for the interaction of investor sophistication (IO) with firm complexity (Conglo) in all of our analyses and document that our main finding cannot be explained by differences in the average investor sophistications of single-segment and multi-segment companies.

In Table 4 we take a step further and analyze the joint impact of innate business complexity and investor sophistication on PEAD. In doing so, every quarter we sort stocks into quintiles based on their institutional ownership percentage, our proxy for investor sophistication. Then, we run our basic regression separately in each quintile. Our results indicate that in quintiles 1 and 2 with low investor sophistication PEAD is economically and statistically larger for conglomerates than single segment firms, in quintiles 3 and 4 it is economically larger but statistically not significantly different, and in quintile 5, where investor sophistication is at its highest, PEAD for conglomerates is statistically not different from the PEAD for single segment firms. While using smaller sub-sections of the sample may reduce the statistical significance of the interaction term, there is a clear pattern in our results. As investor sophistication increases the PEAD differential between conglomerates and single-segment firms is reduced. Our results suggest that for the sub-section of firms with the largest institutional ownership, sophisticated investors can help fully eliminate the adverse effects of innate business complexity on mispricing.

4.4 Controlling for Announcement Effects and Comparison of Delayed Response Ratios

One possible explanation for why complex firms have stronger PEAD is that the information revealed by complex firms on the announcement day takes longer to diffuse. However, an alternative explanation would suggest that, for the same level of earnings surprise, more information is revealed to the market on the announcement day in the case of more complicated firms. If this indeed is the case, then we should see a stronger response around the announcement event followed by a stronger drift for firms with more innate business complexity. Empirically, the alternative scenario would suggest that regressing announcement returns (CAR(-1;1)) as well as the post earnings announcement drift returns (CAR(2;60)) on the interaction of SUE and innate business complexity, would both yield a positive coefficient.

In Panel A of Table 5, we perform OLS regressions of announcement returns (CAR(-1;1)), PEAD returns (CAR(2;60)) as well as total earnings reaction returns (CAR(-1;60)) on the top decile earnings surprise dummy (SUETop), its interactions with Conglo, market-to-book (MB), size (Size), institutional ownership (IO), loss dummy (Loss), illiquidity (Amihud) and analyst coverage (# Analysts) as well as the control variables themselves. Following our approach in Table 3, we exclude microcaps from the sample. SUETop is 1 for the top SUE decile and 0 for the bottom SUE decile[21] and helps us capture hedge returns to going long on the highest SUE decile and going short on the lowest SUE decile.

Column (1) in the Panel A of Table 5 reveals that the interaction of SUETop with Conglo is almost zero (-0.002) and statistically insignificant (t-stat of -0.66). This finding indicates that single-segment firms and conglomerates have similar hedge returns in the three days around earnings announcements. On the other hand, column (2) clearly indicates that a hedge strategy of going long on the highest SUE decile and going short on the lowest SUE decile would net larger returns for conglomerates than single-segment firms as the interaction of SUETop and Conglo is economically (1.5% per quarter) and statistically significant (t-stat of 2.12). In fact, the coefficient on the interaction of SUETop with Conglo is comparable in economic magnitude to the coefficient on SUETop itself, 0.022 vs 0.015, revealing the significant impact innate business complexity has on the level of post earnings announcement drift returns. Finally, column (3) shows that overall stock return responses in announcement plus post-announcement periods are significantly greater for conglomerates. Taken together, results in Panel A of Table 5 suggest that while conglomerates see more information revealed at earnings announcements (see the total response in column 3), the incorporation of all extra information is delayed till the post-announcement period (see equal announcement effects in column 1), i.e., stronger PEAD for conglomerates comes from delayed reaction.

Next, following DellaVigna and Pollet (2009), we quantify the magnitude of the earnings surprise under-reaction for conglomerates. We utilize columns (2) and (3) in Panel A to estimate what fraction of information in the earnings announcement is incorporated into stock prices outside of the earnings announcement window. In Panel B, we calculate the ratio of the drift return, CAR(2,60), to

[21] As in DellaVigna and Pollet (2009), firms outside of the top and bottom SUE deciles are excluded from this analysis; the analysis is effectively the analysis of the ten-minus-one hedge decile return spread in returns.

the total earnings reaction return, CAR(-1,60), to measure the delayed response ratio for single-segment firms and conglomerates. For single segment firms we calculate the delayed response ratio by dividing the coefficient on SUETop (0.022) in column (2) by the coefficient on SUETop (0.050) in column (3), while the delayed response ratio of conglomerates is the ratio of the sum of coefficients on SUETop (0.022) and SUETop*Conglo (0.015) in column (2) to the sum of coefficients on SUETop (0.050) and SUETop*Conglo (0.014) in column (3). Standard errors are calculated using the Delta method as the delayed response ratio is calculated using parameters from two different models.

Finally, we calculate the difference in the delayed response ratios for single-segment firms and conglomerates for a hedge portfolio that trades in extreme positive (negative) surprise earnings deciles. We find that the delayed response ratio for this hedge trade is 59.1% (44.5%) for conglomerates (single-segment firms), which is 14.6% more than it is for the delayed response ratio faced by single-segment firms.[22] Our analysis lends further support to the interpretation that investors have more difficulty processing earnings related information regarding conglomerates and that information processing takes more time for complex firms. The portfolio approach adopted to measure the delayed response ratio also makes it clear that it is indeed possible to trade on stronger PEAD for conglomerates.

4.5 Impact of Changes to Organizational Form on the Post Earnings Announcement Drift

While all proxies for limits to arbitrage we considered are negatively related to innate business complexity and therefore cannot explain our finding that PEAD is stronger for complex firms, it is still possible that complexity and conglomerate status in particular are related to a certain unknown variable that in turn affects the strength of PEAD.

In an effort to understand if investors really have difficulty interpreting information related to more complicated firms, we focus on periods during which innate business complexity increases. If the level of innate business complexity (conglomerate status) is related to a certain unknown variable X that also drives PEAD, then new conglomerates would likely have little exposure to this variable and one would expect new conglomerates to have low levels of PEAD. Indeed, if firms become conglomerates once X exceeds a certain threshold (and conglomerates disband after X dips under the threshold), new conglomerates will have values of X higher than, but close to the threshold, while old conglomerates will also have X above the threshold, but can have X exceed the threshold by a

[22] We use more than three decimal points when calculating the ratio.

lot. Under the complexity hypothesis, however, investors should have the greatest confusion when interpreting earnings announcements of new conglomerates, due to the significant and recent change to their complexity level.[23]

In Table 6, we use a dummy variable for the change in the conglomerate status called NewConglo. NewConglo is set to one in the year after the firm switches from having one segment to having more than a single segment, continues to be one for another year, and becomes zero afterwards. NewConglo is also zero in all years when the firm has only one segment. In an average year, we have about 5,000 firms with segment data, about 1,300 conglomerates, and 120-200 new conglomerates, for which NewConglo is 1. Thus, new conglomerates comprise 2.5-4% of our sample and 10-15% of all conglomerates.

The first column presents our baseline regression from column (3) of Table 3 (post-announcement CAR on SUE, the Conglo dummy, Size, MB and the interactions of SUE with Size, MB and Conglo) with the NewConglo dummy and its interaction with SUE added.[24] The slope on the product of SUE and NewConglo estimates the extra PEAD experienced by new conglomerates as compared to existing conglomerates, since Conglo is, by definition, always 1 when NewConglo is 1.

We make two important observations based on the analysis conducted in the first column of Table 6. First, PEAD experienced by existing conglomerates (firms that have been conglomerates for more than two years) is more than twice the PEAD experienced by single-segment firms. The regression estimates suggest that PEAD is 1.31% (per three months after the announcement) for single-segment firms and 2.32% for existing conglomerates when we use the difference between the 95th and the 5th percentiles of SUE (see Panel A1 of Table 1) to calculate differences in PEAD.[25]

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[23] We argue that changes to X are associated with organizational structure, i.e. when X exceeds a certain threshold the firm becomes a conglomerate. Conglomeration is not the cause of change in X but rather the change in X leads to conglomeration. There could be a different type of omitted variable Y, separate from X, such that it can increase in response to conglomeration and then subside. If such a Y variable is also associated with higher PEAD's, then PEAD's would be stronger for new conglomerates. We argue in this paper that Y is firm complexity. Nevertheless, we acknowledge that there could be some alternative Y that behaves similar to firm complexity but is fundamentally different. While acknowledging that such a Y may offer an alternative explanation of the association between innate business complexity and PEAD we conclude that it is almost impossible to control for all such alternative scenarios. In conclusion we do not claim to solve all omitted variables problems.

[24] Since the number of new conglomerates is low, in Table 6 we do not use the extra controls from Table 3 and elsewhere. Requiring that new conglomerates have non-missing institutional ownership and analyst coverage data leaves us, in some years, with new conglomerates numbering in low double-digits and even in single digits.

[25] The estimates of PEAD would be roughly twice in magnitude for both single-segment firms and existing conglomerates if we instead use the difference between the 97.5th and the 2.5th percentiles of SUE. These numbers are slightly different

We conclude that controlling for the effect of new conglomerates does not reduce the significance of the interaction term between PEAD and the conglomerate dummy. The interaction term is as strong as it is in Table 3, which suggests that stronger PEADs for more complex firms cannot be attributed solely to firms that recently have become conglomerates.

Second, we do find that PEAD is significantly stronger for new conglomerates than it is for single-segment firms as well as it is for existing conglomerates. The product of SUE and NewConglo dummy is statistically significant and its coefficient implies that for new conglomerates PEAD is 4.7% per three months, almost double that of existing conglomerates and more than four times that of single-segment firms.

How are new conglomerates created? In roughly two-thirds of the cases, we are able to trace the increase in the number of segments to M&A activity using SDC data.[26] In the other one-third of the cases it appears that the firm expands from within, starting a new line of business inside the firm.

In the next two columns we try to estimate the PEADs of new conglomerates formed through acquisitions (we replace NewConglo with NewCongloM&A, which equals one only if the change in the conglomerate status can be attributed to a merger with a firm from a different two-digit SIC code on SDC) and the PEADs of new conglomerates created from within (replacing NewConglo with NewCongloNoM&A, which equals one only if the change in the conglomerate status cannot be traced back to a corresponding merger).

We do not have a strong prior regarding whether becoming a new conglomerate through M&A activity or via expansion from within leads to more confusion on the part of investors. On the one hand, the segment added through M&A activity is more likely to be completely new to the firm (whereas the new line of business could have been developing within the firm for several years before the firm starts reporting it as a separate segment) and firms may prefer to expand through M&A activity when venturing into more "distant" industries. These considerations would suggest that stronger PEADs for new conglomerates would be more attributable to new conglomerates formed through M&A activity. On the other hand, both the acquirer and the target receive a lot of scrutiny during a merger, and the target also has a history as a stand-alone firm before the merger. Such

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from our earlier interpretation of Table 3 as in Table 6, we use a smaller set of control variables so the sample is different from the sample used in Table 3.

[26] SDC data includes both public and private firms; while all our buyers are public companies. When we track cases of adding a new segment to SDC, we include acquisitions of both public and private targets as potential ways of adding a new segment through merger and acquisition activity (M&A).

scrutiny and the availability of historical information about the target might suggest that higher PEADs for new conglomerates might be driven by new conglomerates that are formed via expansion from within rather than those that are formed through M&A activity.

Results strongly support the latter view. In column (2), which singles out new conglomerates that are created through mergers, we find that PEAD is higher only by 0.5% per three months for these new conglomerates than it is for existing conglomerates (the difference, measured by the slope on the product of SUE and NewCongloM&A, is statistically insignificant). In column (3) though, we focus on new conglomerates that are created from within (i.e., not through a merger), and we discover a huge difference in the PEADs of these new conglomerates and the PEADs of existing conglomerates. Substituting the difference in SUE between the 95th and the 5th percentiles into the regression in the third column, we estimate the average PEAD for single-segment firms at 1.1% (per three months after the announcement), the average PEAD of existing conglomerates at 2.3%, and the average PEAD of new conglomerates created from within at a whopping 8.8%. We conclude therefore that the stronger average PEAD for firms that have recently become conglomerates is attributable primarily to firms that have created a new line of business from within, without merging with another firm from a different industry.

Results in Table 6 strongly suggest that the increase in complexity (defined as the change in the conglomerate status) is associated with a large increase in PEAD, consistent with our hypothesis that it is firm complexity (and not any other characteristic common to conglomerates) that creates stronger PEAD. We also find that investors are most confused about firms that expand from within, i.e. about those firms that add segments without being involved in M&A activity.

4.6 Does the Degree of Complexity Matter? Using Hirshleifer and Teoh (2003) Measure

In the previous sections we have established that there is a strong relationship between organizational structure and the strength of PEAD. In this section we investigate if PEAD is stronger for more complicated conglomerates. In doing so we construct a measure proposed by Hirshleifer and Teoh (2003) that enables us to rank conglomerates based on their level of complexity.

Hirshleifer and Teoh (2003) suggest that the high cognitive processing costs associated with analyzing earnings growth at the segment level lead at least some investors to focus on aggregated information even if segment level data are available. They propose that even if only some investors use aggregate firm earnings growth rates to estimate future firm values, instead of using segments' individual earnings growth rates, these conglomerates will be mispriced. Hirshleifer and Teoh (2003) interpret the dispersion of the segment growth rates as a measure of high cognitive processing costs due to harder-to-process nature of such information. They suggest that the level of mispricing (cognitive processing costs) will increase with the dispersion of the segment growth rates.

We construct a new empirical proxy of conglomerate complexity following Hirshleifer and Teoh's (2003) measure of cognitive processing costs. We call this measure HTSD (Hirshleifer-Teoh-Segment-Dispersion) and calculate it as $HTSD = \sum_{i=1}^{N}(E_i - f)^2 * S_i$, for a firm with N segments that has an aggregate earnings growth rate of f, where each segment i has growth rate E_i, and sales share as a percentage of the firm's total sales which is equal to S_i. We also compute log of one plus HTSD, LogHTSD, to account for HTSD's high skewness.

In Table 7, we focus our analysis on the conglomerate-only sample and investigate if conglomerates with higher HTSD have higher PEAD. In the first column of Table 7, controlling for the effects of size and market-to-book and their interactions with SUE, we analyze the interaction of HTSD with SUE and find that conglomerates with greater segment earnings growth dispersion have larger post-earnings announcement drifts compared to other conglomerates for the same level of SUE.[27] The interaction term is 0.154 and statistically significant. The interaction term indicates that the PEAD returns between the 97.5th and the 2.5th SUE percentiles for a conglomerate that is in the top decile based on the segment growth dispersion measure[28] would be 1.36% more than the PEAD returns between the 97.5th and the 2.5th SUE percentiles for a conglomerate that is in the bottom decile based on the HTSD measure. In column (2) of Table 7 we repeat the same analysis using LogHTSD and reach similar qualitative and quantitative conclusions.

Results in Table 7 are in clear agreement with the theoretical deductions of Hirshleifer and Teoh (2003). Investors have more difficulty understanding earnings related information regarding conglomerates with larger dispersion in their segment earnings growth rates. Our results indicate that market participants take longer to incorporate earnings related information into the prices of more complicated conglomerates in line with Hirshleifer and Teoh's (2003) suggestion that innate business complexity introduces cognitive processing costs. These results also help establish the fact that the

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[27] As in Table 6 we have a limited number of independent variables also in Table 7 due to sample size restrictions. Including investor sophistication (IO), Loss, Amihud, # Analysts would have left us with too few observations to carry out the required analyses.

[28] The average for HTSD is 0.19 among conglomerates. The 90th percentile value of HTSD is 0.336 while the 10th percentile value for HTSD is 0.013.

degree of complexity also matters in determining the magnitude of PEAD as there is cross-sectional variation in the magnitude of PEAD with respect to business complexity in a universe of firms composed solely of conglomerates.

5. ROBUSTNESS TESTS

5.1 Controlling for Potential Spillover from Industry-wide Information Events on PEAD

The return predictability documented by Cohen and Lou (2012), though clearly different from our result, can potentially overlap with it in the following way: if the industries the conglomerate operates in are doing well in month t-1, the conglomerate is more likely to report good earnings in month t. If the earnings are particularly good, they will be followed by the post-announcement drift. However, part of this drift, at least in the first month (month t), can be explained by good returns to the pseudo-conglomerate in month t-1. Thus, the predictability documented by Cohen and Lou (2012) can potentially explain why PEAD is stronger for conglomerates.

Our prior is that the overlap between our result and the Cohen and Lou result is not strong. First, Cohen and Lou show that their predictability of conglomerate returns in month t using pseudo-conglomerate returns in month t-1 is attributable primarily to the first two weeks of month t. Since an average earnings announcement happens in the middle of the month, it would be fair to say that we will be missing those two weeks most of the time. Second, the predictability in Cohen and Lou (2012) lasts for only one month, whereas the stronger PEAD for conglomerates lasts throughout the quarter.[29]

In Table 8, we explicitly control for pseudo-conglomerate returns (PCRet) by adding it to our main regressions of CARs on SUE, complexity, the usual list of controls, the interaction of SUE and complexity as well as the interactions of SUE with the list of controls. Following Cohen and Lou, PCRet is computed by first taking an equal-weighted average return of all single-segment firms in each two-digit SIC industry, and then, for each conglomerate, value-weighting the industry returns by the fractions of the segments with the same two-digit SIC code that comprise the total sales of the conglomerate.

Since our sample has to include both single-segment firms and conglomerates in order to compare the PEADs for the two types of firms, we have to substitute an alternative variable for

[29] In unreported results we find that the larger drift experienced by more complicated firms is not confined to the first month of the quarter. Results are available upon request.

"PCRet" for single-segment firms. We define "PCRet" of single-segment firms as the lagged return to single segment firms in the same industry, thus turning it into a measure of industry momentum.[30]

In the first column of Table 8, we regress CARs on SUE, PCRET itself as well as the interaction of PCRet with Conglo and our standard set of controls from Table 3. We control for both PCRet itself and the interaction of PCRet with the conglomerate dummy, to allow for different slopes on it for single-segment firms and conglomerates. In column (1) we observe that PCRet itself is insignificant, while its product with the conglomerate dummy is statistically significant. In the second column of Table 8, we add the interaction of SUE with Conglo to the list of controls which eliminates the statistical significance of the interaction between PCRET and Conglo. The other two columns of Table 8 add to the regression alternative measures of complexity, namely Comp in column (3) and NSeg in column (4), and their interactions with SUE. The slopes on the interactions of complexity with SUE estimate the additional PEAD experienced by conglomerates. The slopes estimated after controlling for the predictability documented in Cohen and Lou (2012) are similar in magnitude to the slopes estimated earlier in Table 3. We conclude that the stronger PEADs experienced by conglomerates is a separate phenomenon that has no overlap with the predictability of conglomerate returns using returns to pseudo-conglomerates as suggested by Cohen and Lou (2012).

5.2 Controlling for Alternative Explanations of PEAD

In Table 1, Panel C, and Table 2, Panel B1, we show that conglomerates face lower trading costs and lower limits to arbitrage compared to single-segment firms. Hence, higher PEADs for more complicated firms cannot be explained by limits-to-arbitrage proxies used in Bartov, Radhakrishnan and Krinsky 2000; Mendenhall 2004; Ng, Rusticus, and Verdi 2008; Sadka 2006.

In Table 9, we control for the potential impact of a large number of alternative explanations of the post-earnings announcement drift anomaly using Fama-Macbeth (1973) style regressions. In particular, we control for the impact of the time-varying nature of earnings persistence (Chen 2013), the impact of disclosure complexity (Miller 2010, You and Zhang 2009, Feldman, Govindaraj, Livnat, and Segal 2010, Lehavy, Li and Merkley 2011, Lee 2012), analyst responsiveness (Zhang 2008) as well as the impact of ex-ante earnings volatility on earnings persistence (Cao and

[30] Strictly speaking, the correct way to estimate industry momentum would be to compute industry returns using all firms in the industry, including conglomerates. We tried that and found little change in the slope of "PCRet" for single-segment firms defined this way, which suggests that the average return to all single-segment firms in an industry is a good enough proxy for the true industry return.

Narayanamoorthy 2012) on PEAD in an effort to distinguish the impact of innate business complexity on PEAD.

The first column in Table 9 estimates the relation between PEAD and conglomerate status controlling for the effect of Size, MB, conglomerate status and the interaction of SUE with Size and MB respectively. We use the results in column (1) of Table 9 as a benchmark for the other columns in Table 9.[31]

In the second column of Table 9, we repeat the basic analysis conducted in column (1) for a subsample of firms for which we can calculate the time-varying earnings persistence variable (EP) proposed by Chen (2013).[32] Results are qualitatively and quantitatively comparable to full-sample results. In column (3) we estimate the relation between PEAD and conglomerate status controlling for time-varying earnings persistence (EP) and its interactions with SUE. We find that the interaction of SUE with EP has the predicted positive sign documented by Chen (2013). Controlling for the interaction of SUE with EP reduces the loading on the interaction term between SUE and the conglomerate dummy approximately by 20%. While this indicates that there could be some overlap between the effect of time-varying earnings persistence introduced by Chen (2013) and business complexity, this overlap is not large enough to negate the higher PEAD we observe in conglomerates.

The fourth and fifth columns investigate the impact of innate business complexity on PEAD while controlling for the impact of disclosure complexity. Our proxy for disclosure complexity is the Gunning FOG index calculated as in Li (2008).[33] In column (4), we investigate the impact of innate business complexity on PEAD for the sub-set of firms for which we have textual complexity information. Column (4) reveals results consistent with our basic findings, as conglomerates have higher PEADs compared to single-segment firms with similar characteristics in this sub-sample as well. In column (5) we find a surprising result. The interaction of SUE with FOG, our proxy for disclosure complexity, is negative and statistically marginally insignificant suggesting that the post-

[31] In Table 9, we only use Size and MB as controls, as requiring non-missing variables of other controls from Table 3 (such as analyst coverage and institutional ownership) would significantly reduce the number of conglomerates in some years in several columns of Table 9.

[32] Earnings Persistence (EP) is the firm-specific time-varying autocorrelation between two adjacent quarterly seasonally differenced earnings (SDE), where the autocorrelation is estimated in a two-step procedure using 14 persistence-related firm characteristics each quarter following Chen (2013).

[33] We got the data from Feng Li's website, for which we are grateful.

earnings announcement drift anomaly in fact could be smaller for firms with higher disclosure complexity. We believe this result could potentially indicate that the interaction of FOG with SUE is more likely to capture the impact of managerial obfuscation on PEAD, rather than the impact of firm complexity.[34] Controlling for FOG doesn't affect our results as the interaction of SUE with Conglo in column (5) is statistically and economically significant and virtually indistinguishable from the results in column (4).

In columns (6) and (7), we analyze whether varying analyst responsiveness for conglomerates and single-segment firms could explain our results. Following Zhang (2008), we construct a measure of analyst responsiveness (DRESP) and investigate whether its interaction with SUE could reduce the economic and statistical impact of business complexity on PEAD. Column (6) reveals that our basic results go through for the sub-sample of firms with available DRESP information. In column (7), we find that the interaction of SUE with DRESP is negative, qualitatively in line with Zhang (2008)'s prediction that more responsive analysts help investors react to earnings more timely and this leads to a reduction in PEAD.[35] Controlling for the impact of analyst responsiveness does not change our basic result regarding the impact of innate business complexity on PEAD as the interaction of SUE with Conglo is once again statistically and economically significant and positive.

In a recent paper, Cao and Narayanamoorthy (2012) show that, contrary to the expectations of the market, firms with higher ex-ante (lower) earnings volatility (trading frictions) have lower (higher) earnings surprise (SUE) persistence and this leads to lower PEAD. Since conglomerates, on average, have smaller earnings volatility (EarnVol) and fewer overall trading frictions it is imperative that we control for this effect. In column (8), we analyze the impact of organizational structure on PEAD for a subset of firms for which we have ex-ante earnings volatility, calculated as in Cao and Narayanamoorthy (2012). We find that our results are virtually the same as the full-sample results as conglomerates have larger PEADs for the same level of SUE compared to single-segment firms. In column (9) we explicitly control for the impact of ex-ante earnings volatility on PEAD. Our results are consistent with Cao and Narayanamoorthy (2012), since higher ex-ante earnings volatility leads to lower PEAD, as evidenced by the economically and statistically significant negative coefficient on

[34] Future research may attempt to decompose FOG into innate business-complexity and managerial obfuscation components as in Bushee et al. (2015) and analyze the impact of these components on PEAD separately.

[35] Unlike Zhang (2008), however, our interaction term is statistically insignificant. We attribute this difference mainly to methodology. When we use panel regressions, instead of Fama-MacBeth (1973) style regressions, the interaction term becomes significant.

the interaction of SUE and EarnVol. This, however, barely affects our main finding as the interaction of SUE with Conglo is 0.094 and statistically significant. This leads us to conclude that our result about the impact of innate business complexity is distinct from the impact of ex-ante earnings volatility on PEAD.

Finally, in column (10) we control for the impact of MB, Size, Conglo, EP, FOG, DRESP and EarnVol along with their interactions with Conglo and find that the interaction of SUE with Conglo is statistically and economically significant, verifying the distinctiveness of the effect we have uncovered in this paper.

5.3 Accounting for Non-Linearity in SUE and Using Alternative CAR Measures

In our final robustness section we use an alternative measure of abnormal returns namely four-factor Carhart alphas. In Table 10, we repeat our basic analysis from Table 3 using Carhart alphas on three alternative measures of unexpected earnings surprise along with three alternative measures of firm complexity (Conglo, Comp, NSeg) for a total of nine regressions. In particular, we run quarterly Fama-MacBeth regressions of firm-specific Carhart alphas cumulated in the 60 trading days (one-quarter) following earnings announcements ($\alpha C(2;60)$) on earnings surprise (SUE), interactions of SUE with the measures of firm complexity (Conglo, Comp and NSeg) and with standard controls (MB, Size, IO, Loss, Amihud and # Analysts) and their interactions with SUE.

Columns (1) to (3) use the baseline definition of SUE, where we winsorize SUE at 99.5% and 0.5% percentile levels every given quarter in order to account for the non-linear relation between SUE and future returns. In columns (4) to (6) we winsorize SUE at 95% and 5% percentile levels in a given quarter to account for both the non-linearity mentioned earlier as well to eliminate the possibility that extreme SUE values drive our results. Finally, in columns (7) to (9) we transform SUE into decile ranks to verify that our main result in this paper leads to a profitable trading strategy.

In column (1) of Table 10, we find that the interaction of SUE with Conglo is virtually unchanged in our basic specification when we replace Size and BM adjusted returns with Carhart-alphas. Similarly, columns (2) and (3) reveal that interactions of SUE with Comp and NSeg, respectively, yield very similar results to those observed in Table 3, suggesting that whether we use Size and BM adjusted returns or Carhart alphas, we find larger PEADs for more complicated firms.

Similarly, winsorizing SUE values at the 5^{th} and 95^{th} percentiles every quarter does not change our results. In columns (4) through (6) we find that the interaction of SUE with measures of innate business complexity are all positive and economically as well as statistically significant leading to higher PEADs. Results in columns (4) through (6) suggest that our results are not driven by extreme values of SUE.

Finally, in columns (7) through (9) we repeat our basic Fama-MacBeth (1973) regressions using Carhart alphas and decile values for SUE. Our conclusions are unchanged as these regressions also predict higher PEAD values for firms with more complicated underlying businesses. Results in columns (7) through (9) add further evidence to the tradability of this strategy as it utilizes decile portfolios.

6. CONCLUSIONS

In this paper, we hypothesize and document that information about complex firms is harder to process, and predict therefore that PEAD is stronger for complex firms. Using organizational structure as our proxy for innate business complexity, we find that firms with more complicated organizational structures (conglomerates) have larger post-earnings announcement drifts (PEADs) compared to simpler firms (single-segment firms) with the same level of unexpected earnings surprise (SUE). Specifically, we find that conglomerates have PEADs that are at least twice as large as single-segment firms. The impact of complexity on PEAD lasts for at least two months, which leads us to conclude that investors of complex firms have even more trouble interpreting earnings-related information than they do interpreting industry-wide shocks (as Cohen and Lou, 2012, find, conglomerates incorporate industry-wide shocks with a delay of two-to-four weeks). We investigate whether the phenomenon documented in this paper is related to the return predictability documented in Cohen and Lou (2012). We control for pseudo-conglomerate returns in our regressions and find that the interaction between SUE and innate business complexity is unaffected, which means that there is virtually no overlap between the Cohen and Lou (2012) result and the stronger PEAD for conglomerates.

Our findings cannot be explained by limits-to-arbitrage (studied in Bartov, Radhakrishnan and Krinsky 2000; Mendenhall 2004; Ng, Rusticus, and Verdi 2008; Sadka 2006) as conglomerates on average are larger than single-segment firms and have lower limits to arbitrage. We include interactions of SUE with several limits-to-arbitrage variables as controls and our main results are still intact. Thus, we attribute our findings to the fact that it is more costly and difficult to understand firm-specific earnings information regarding complicated firms and that information processing takes more time for complex firms, leading conglomerates to underreact to earnings surprises significantly more than single-segment firms. In order to assess how innate business complexity impacts information production, we control for size by comparing conglomerates to single-segment firms of similar size. We document that, once we control for firm-size and other fundamental firm characteristics, conglomerates have relatively low institutional ownership and lower short interest, relatively low segment disclosure quality, are covered by fewer analysts, these analysts have less industry expertise and they also make larger forecast errors.

Next, we investigate whether conglomerates release more news for the same level of unexpected earnings surprise (SUE) compared to single-segment firms. We find that the announcement reaction is very similar for single-segment firms and conglomerates, which, coupled with the stronger PEAD for conglomerates, implies that the total amount of information released at earnings announcements is larger for conglomerates. However, all this extra information seems to be absorbed in the post-announcement window. We also find that conglomerates underreact to earnings surprises more than single-segment firms as evidenced by larger delayed response ratios for conglomerates (59.1%) compared to single-segment firms (44.5%). Our analysis lends further support to the interpretation that investors have more difficulty processing earnings related information regarding conglomerates and that information processing takes more time for complex firms.

To address the concern that complexity is related to a certain unknown variable that also affects the strength of PEAD, we re-examine the effect of complexity on PEAD focusing on periods during which firm complexity increases. The analysis provides compelling evidence that supports our slower-information-processing hypothesis: PEAD is stronger for new conglomerates than it is for existing conglomerates. We also find that investors are most confused about complicated firms that expand from within rather than firms that diversify into new business segments via mergers and acquisitions (and receive significant public scrutiny in the process). We further conduct an investigation of Hirshleifer and Teoh's (2003) theoretical prediction that more complicated conglomerates, measured as those with greater dispersion in the growth rates of their segment level earnings, face larger mispricing. We find that more complicated conglomerates have larger PEADs than less complicated conglomerates. Our analysis indicates that the degree of complexity influences the level of PEAD and that the cognitive cost of processing more complicated segment-level information leads to larger PEADs for more complicated conglomerates.

Our results are robust to controlling for the impact of analyst responsiveness, ex-ante earnings volatility, time-varying earnings persistence and disclosure complexity on PEAD. Not only that, but we also document that our results go through when we use Carhart-alphas instead of size and book-to-market adjusted returns and that our conclusions are robust to alternative definitions of SUE such as using SUE values winsorized at .5% (99.5%/0.5%), 5% (95%/5%) or simply using SUE deciles.

We conclude that innate business complexity, proxied via organizational structure, has a profound effect on how investors process earnings related information. Our analyses document that investors face larger cognitive processing costs regarding conglomerates which leads to larger post-earnings announcement drifts for firms with complicated underlying businesses.

References

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, Journal of Financial Markets, v. 5, pp. 31-56

Barinov, Alexander, 2018, Firm Complexity and Conglomerates Expected Returns, Working Paper, University of California Riverside

Barinov, Alexander, and Julie Wu, 2014, High Short Interest Effect and Aggregate Volatility Risk, Journal of Financial Markets, v. 21, pp. 98-122

Bartov, Eli, Suresh Radhakrishnan, and Itzhak Krinsky, 2000, Investor Sophistication and Patterns in Stock Returns after Earnings Announcements, The Accounting Review, v. 75, pp. 43-63

Berger, Philip G. and Eli Ofek, 1995, Diversification's Effect on Firm Value, Journal of Financial Economics, v. 37, pp. 39-65

Bushee, Brian, Ian Gow, and Daniel Taylor, 2018, Linguistic Complexity in Firm Disclosures: Obfuscation or Information, Journal of Accounting Research, v. 56, pp. 85-121

Cao, Sean and Ganapathi Narayanamoorthy, 2012, Earnings Volatility, Post–Earnings Announcement Drift, and Trading Frictions, Journal of Accounting Research, v. 50, pp. 41–74

Chemmanur, Thomas, and Mark Liu, 2011, Institutional Trading, Information Production, and the Choice Between Spin-offs, Carve-outs, and Tracking Stock Issues, Journal of Corporate Finance, v. 17, pp. 62-82

Chen, Changling, 2013, Time-Varying Earnings Persistence and the Delayed Stock Return Reaction to Earnings Announcements, Contemporary Accounting Research, v. 30, pp. 549–578

Chordia Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam, 2007, The Cross-Section of Expected Trading Activity, Review of Financial Studies, v. 20, pp. 709-741

Clement, Michael, 1999, Analyst forecast accuracy: Do Ability, Resources, and Portfolio Complexity Matter? Journal of Accounting and Economics, v. 27, pp. 285-303

Cohen, Lauren, and Dong Lou, 2012, Complicated Firms, Journal of Financial Economics, v. 104, pp. 383-400

Corwin, Shane A., and Paul Schultz, 2012, A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices, Journal of Finance, v. 67, pp. 719-759

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, Journal of Finance, v. 52, pp. 1035-1058

DellaVigna, Stefano, and Joshua Pollet, 2009, Investor Inattention and Friday Earnings Announcements, Journal of Finance, v. 64, pp. 709-749

Duru, Augustine, and David M. Reeb, 2002, International Diversification and Analysts' Forecast Accuracy and Bias, The Accounting Review, v. 77, pp. 415-433

Fama, Eugene F., 1976, Foundations of Finance, Basic Books

Fama, Eugene F., and James MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, Journal of Political Economy, v. 81, pp. 607-636

Feldman, Ronen, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal, 2010, Management's Tone Change, Post Earnings Announcement Drift and Accruals, Review of Accounting Studies, v. 15, pp. 915-953

Franco, Francesca, Oktay Urcan, and Florin Vasvari, 2016, Corporate Diversification and the Cost of Debt: The Role of Segment Disclosures, The Accounting Review, v. 91, pp. 1139-1165

Gilson, Stuart, Paul Healy, Christopher Noe, and Krishna Palepu, 2001, Analyst Specialization and Conglomerate Stock Breakups, Journal of Accounting Research, v. 39, pp. 565–582

Gleason, Cristi A. and Charles M. C. Lee, 2003, Analyst Forecast Revisions and Market Price Discovery, The Accounting Review, v. 78, pp. 193-225

Gompers, Paul A., and Andrew Metrick, 2001, Institutional Investors and Equity Prices, Quarterly Journal of Economics, v. 116, pp. 229-259

Hasbrouck, Joel, 2009, Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data, Journal of Finance, v. 64, pp. 1445-1477

Hilary, Gilles, and Rui Shen, 2013, The Role of Analysts in Intra-Industry Information Transfer, The Accounting Review, v. 88, pp. 1265-1287

Hirshleifer, David and Siew Teoh, 2003, Limited attention, information disclosure, and financial reporting, Journal of Accounting and Economics, v. 36, pp. 337-386

Hirshleifer, David, Seongyeon Sonya Lim, and Siew Teoh, 2009, Driven to Distraction: Extraneous Events and Underreaction to Earnings News, Journal of Finance, v. 64, pp. 2289-2325

Hong, Harrison, Terence Lim, and Jeremy Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, Journal of Finance, v. 55, pp. 265-295

Lang, Larry and René Stulz, 1994, Tobin's q, Corporate Diversification and Firm Performance, Journal of Political Economy, v. 102, pp. 1248-1280

Lee, Charles M.C. and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, Journal of Finance, v. 55, pp. 2017-2069

Lee, Yen-Jung, 2012, The Effect of Quarterly Report Readability on Information Efficiency of Stock Prices, Contemporary Accounting Research, v. 29, pp. 1137–1170

Lehavy, Reuven, Feng Li, and Kenneth Merkley, 2011, The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts, The Accounting Review, v. 86, pp. 1087-1115

Lesmond, David A., Joseph Ogden, and Charles Trzcinka, 1999, A New Estimate of Transaction Costs, Review of Financial Studies, v. 12, pp. 1113 1141

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The Illusory Nature of Momentum Profits, Journal of Financial Economics, v. 71, pp. 349-380

Mendenhall, Richard, 2004, Arbitrage Risk and Post-Earnings-Announcement Drift, Journal of Business, v. 77, pp. 875-894

Miller, Brian, 2010, The Effects of Reporting Complexity on Small and Large Investor Trading, The Accounting Review, v. 85, pp. 2107-2143

Newey, Whitney, and Kenneth West, 1987, A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica, v.55, pp. 703-708

Ng, Jeffery, Tjomme Rusticus, and Rodrigo Verdi, 2008, Implications of Transaction Costs for the Post–Earnings Announcement Drift, Journal of Accounting Research, v. 46, pp. 661–696

Peterson, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, Review of Financial Studies, v. 22, pp 435-480

Roll, Richard, 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, Journal of Finance, v. 39, 1127-1139

Sadka, Ronnie, 2006, Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk, Journal of Financial Economics, v. 80, pp. 309-349

Thomas, Shawn, 2002, Firm diversification and asymmetric information: evidence from analysts' forecasts and earnings announcements, Journal of Financial Economics, v. 64, pp. 373-396

You, Haifeng, and Xiao-jun Zhang, 2009, Financial Reporting Complexity and Investor Under-reaction to 10-K Information, Review of Accounting Studies, v. 14, pp. 559-586

Zhang, X. Frank, 2006, Information Uncertainty and Stock Returns, Journal of Finance, v. 61, pp. 105-136

Zhang, Yuan, 2008, Analyst Responsiveness and the Post-Earnings-Announcement Drift, Journal of Accounting and Economics, v.46, pp. 201-215

DATA APPENDIX

The variables are arranged in alphabetical order according to the abbreviated variable name used in the tables.

 # Age - Age measures firm age, as in Gompers and Metrick (2001), by counting the number of months since the first return appears in CRSP file.

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

Amihud (Amihud illiquidity 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 firms with stock price less than $5 at the end of the previous year are excluded).

Beta – Beta is the systematic risk exposure to market-risk-premium in the Capital Asset Pricing Model and is calculated using the returns from the past 60 months.

CAR(-1;1) (announcement return) - size and book-to-market adjusted cumulative daily returns between the day prior to the earnings announcement and the day after the earnings announcement. Earnings announcement dates are from COMPUSTAT, daily returns are from CRSP daily files, size and book-to-market adjustment is performed following Daniel et al. (1997).

CAR(2;60) - size and book-to-market adjusted cumulative daily returns between the second day after the earnings announcement and the 60th day after the earnings announcement.

CAR(2;20) (CAR(21;40), CAR(41;60)) - size and book-to-market adjusted cumulative daily returns between the second (21st, 41st) day after the earnings announcement and the 20th (40th, 60th) day after the earnings announcement.

Complexity (firm complexity) - 1-HHI, where HHI is the Herfindahl index computed using segment sales, $HHI = \sum_{i=1}^{N} s_i^2$. N is the number of segments (from Compustat segment files, 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.

Conglo (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.

Div (dividend payout ratio) – Dividend payout ratio is the ratio of dividends paid out to shareholders scaled by net income.

Forecast dispersion – Forecast dispersion is the standard deviation of all earnings per share (EPS) forecasts, scaled by the absolute value of mean EPS forecasts.

Forecast error - Forecast Error is the absolute value of the difference between consensus earnings forecast and actual earnings, scaled by actual earnings.

GeoMulti (Geographic complexity) - GeoMulti, measuring geographic complexity, is a dummy variable equal to one if the firm generates its sales from a multitude of geographic segments and zero if the firm generates all of its sales from the same geographic segment. In calculating GeoMulti, we use Compustat segment files.

Gibbs (Gibbs measure) - the slope from the regression $\Delta P_t = a + c\Delta Q_t$, where P_t is the stock price and Q_t is the trade direction indicator. The values of the Gibbs measure are taken from the website of Joel Hasbrouck and are available from January 1964 to December 2009. For more details, please refer to Hasbrouck (2009).

Intan (intangible asset ratio) - Intan is the log of one plus the ratio of intangible assets to total assets.

IO (institutional ownership) - the sum of institutional holdings from Thompson Financial 13F database, divided by the 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 Thompson Financial 13Fs, it is assumed to have zero institutional ownership.

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

Lev (book leverage) - is the book leverage measured by total liabilities divided by total assets

Loss - is an indicator variable equal to 1 if the company incurred an operating loss in the immediate quarter, 0 otherwise.

MB (market-to-book) – MB measures the ratio of market value of equity to book value of equity. Book value of equity reported any time within a given calendar year is calculated following Daniel and Titman (2006). If the fiscal year end falls between January and May, then the MB for, say, calendar year 2005 will be the market value of equity as of Dec 2004 scaled by the book equity reported for the fiscal year 2003. If the fiscal year end falls between June and December, then MB ratios for calendar year 2005 will be the market value of equity of as Dec 2004 divided by book equity in fiscal year 2004.

Mlev (market leverage) – Market leverage is calculated as the ratio of the market value of debt scaled by the summation of market value of debt and market value of equity. We calculate the market value of debt using Merton's (1974) structural model.

Momentum - Momentum is the cumulative return between month -2 and month -12.

Mom1 – Mom1 is the cumulative return in the past three months.

Mom4 – Mom4 is the cumulative return between month -4 and month -12.

NewConglo (new conglomerate dummy) - 1 if the firm became a conglomerate in the past two years (the year of the change in the conglomerate status excluded), zero otherwise. Single-segment firms always have NewConglo=0.

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

PCRet (pseudo-conglomerate return) - For each conglomerate firm, a pseudo-conglomerate consists of a portfolio of the conglomerate firm's segments made up using only stand-alone firms from the respective industries. For each portfolio that corresponds to a specific segment of the conglomerate firm an equal-weighted return is calculated. Returns corresponding to each segment are then value weighted according to that segment's contribution to the conglomerate firm's total revenues in order calculate a corresponding pseudo conglomerate return.

Rdsales (Research and Development expenses to sales) - Rdsales is the ratio of R&D expense to sales.

Res # An, Res # Spec (residual number of analyst/specialists) - the number of analysts/specialists following the firm orthogonalized to size. The orthogonalization is performed by running a cross-sectional regression of the number of analysts/specialists on size in each quarter and taking the residuals.

Ret_t – Ret_t is the annual stock return of the current year.

Ret_{t-1} - Ret_{t-1} measures the annual stock return of the previous year.

Roll (Roll measure) - the estimate of effective bid-ask spread, computed as $Roll_t = 200 \cdot \sqrt{abs(Cov(R_t, R_{t-1}))}$

RSI (Relative short interest) - Relative short interest is equal to outstanding short position divided by the number of shares outstanding.

Segment Disclosure Quality – Segment disclosure quality is the firm's average industry-adjusted (at 2-digit SIC code levels) percentage of segment items reported at the end of the fiscal year and is calculated as described in Corporate Diversification and the Cost of Debt: The Role of Segment Disclosures by Franco, Urcan and Vasvari (2015).

Size – Size is market capitalization.

Snp (S&P 500 membership dummy) – Snp is equal to one if the firm is a member of the Standard and Poor's 500 index, zero otherwise.

 # 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 (# Spec2) or three-digit (# Spec3) 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.

% Spec (percentage of specialists) - the number of specialists following the firm (# Spec) divided by the number of analysts following the firm (# An).

SUE (earnings surprise) - standardized unexpected earnings, computed as

$$SUE_t = \frac{E_t - E_{t-4}}{P_t}$$

where E_t is the announced earnings per share for the current quarter, E_{t-4} is the earnings per share from the same quarter of the previous year, and P_t is the share price for the current quarter.

Size (market cap) - shares outstanding times price, both from the CRSP monthly returns file. Size is measured in billion dollars.

Spread - the spread implied by the daily high and low prices. Spread is calculated by the formula from Corwin and Schultz (2012):

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

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

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

where HI_t (LO_t) is the highest (lowest) price of the stock on day *t*.

Turn (turnover) - monthly dollar trading volume over market capitalization at the end of the month (both from CRSP), averaged in each firm-year.

Vol (volatility) – Vol is the standard deviation of daily stock returns over the fiscal year.

Zero (zero frequency) - the fraction of zero-return days within each firm-year.

Table 1
Descriptive Statistics

Panel A1. SUE and Innate Business Complexity Distribution - All Firms

	# Observations	Mean	Percentiles 1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	381,359	0.010	-0.317	-0.145	-0.075	-0.034	-0.007	0.002	0.008	0.029	0.064	0.129	0.302
Nseg	549,526	1.547	1	1	1	1	1	1.2	2	2.7	3.4	4	4.7
Comp	549,526	0.117	0	0	0	0	0	0.023	0.143	0.449	0.546	0.608	0.678

Panel A2. SUE and Innate Business Complexity Distribution - Conglomerates Only

	# Observations	Mean	Percentiles 1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	111,588	-0.001	-0.271	-0.129	-0.067	-0.031	-0.007	0.002	0.008	0.026	0.053	0.101	0.220
Nseg	146,583	2.646	2	2	2	2	2	2.2	3.1	3.8	4.3	4.9	5.7
Comp	146,583	0.351	0.011	0.021	0.041	0.079	0.191	0.368	0.497	0.596	0.655	0.694	0.736

Panel B. Earnings Announcements

Panel B1. Raw Values	Single	Conglo	S-C	Panel B2. Absolute Values	Single	Conglo	S-C
SUE	0.156%	0.155%	0.001%	**SUE**	0.626%	0.660%	-0.03%
	(6.86)	*(4.03)*	*(0.06)*		*(17.40)*	*(17.20)*	*(-1.52)*
EA	0.137%	0.161%	-0.024%	**EA**	3.575%	2.866%	0.71%
	(2.80)	*(3.17)*	*(-0.59)*		*(12.50)*	*(14.40)*	*(5.67)*
# Observations	269,771	111,588		**# Observations**	269,771	111,588	

Table 1- continued

Panel C. Liquidity			
	Single	**Conglo**	**S-C**
Gibbs	0.540	0.389	0.151
	(13.30)	*(21.90)*	*(4.61)*
# Observations	244,834	103,904	
Spread	0.871	0.599	0.272
	(12.40)	*(13.00)*	*(5.20)*
# Observations	313,595	120,893	
Roll	1.525	1.2	0.325
	(17.80)	*(20.90)*	*(4.95)*
# Observations	320,381	122,410	
Amihud	3.686	2.201	1.484
	(3.73)	*(2.94)*	*(4.76)*
# Observations	163,056	73,220	
Zero	14.09	11.81	2.28
	(5.64)	*(5.87)*	*(3.85)*
# Observations	319,289	121,481	

Note: This table presents mean (Panels A and B) and median (Panel C) values of numerous firm characteristics for single-segment firms (``Single"), and conglomerates (``Conglo") as well as the difference between single-segment firms and conglomerates (S-C). Conglomerates are defined as firms with business segments in more than one industry (industries are based on two-digit SIC codes) with corresponding information in Compustat Segment files, single-segment firms are all other firms with information in Compustat segment files. Innate business complexity, (*Comp*), is 1-HHI, where HHI is the Herfindahl index computed using segment sales within a conglomerate: for each segment, we compute the amount of sales generated by that segment as a fraction of the total sales of the firm and add up the squared fractions to compute HHI. (*Nseg)* is the number of segments the firm has and is an alternative measure of innate business complexity along with (*Conglo)* and (*Comp)*. Segments are counted as distinct business units if they can be assigned to different two-digit SIC industries. (*SUE)* measures surprise unexpected earnings as $(E_t-E_{t-4})/P_t$, where E_t is the announced earnings per share for the current quarter, E_{t-4} is the earnings per share from the same quarter of the previous year, and P_t is the share price for the current quarter. (*EA)* measures earnings announcement reaction in percentage returns. Detailed explanations of *SUE*, *Nseg, Comp, EA* as well as firm level liquidity and information environment variables are in the Data Appendix. The differences for different firm characteristics between *Single* and Conglo firms are calculated quarterly and the time-series averages of these differences are reported in the difference columns. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses in Panels B and C. The sample period is from January 1977 to December 2010. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

Table 2
Comparing the Information Production for Conglomerates and Single-segment firms with similar firm characteristics

Panel A. Information Environment of Single-Segment firms and Conglomerates across size deciles

Panel A1. Single-Segment Firms

Size	**Small**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Big**
# Analysts	1.2	1.5	1.9	2.4	3.0	3.6	4.5	5.7	7.2	11.4
# Specialists SIC2	0.8	1.0	1.4	1.8	2.3	2.9	3.7	4.8	6.3	10.4
# Specialists SIC3	0.6	0.9	1.2	1.5	2.0	2.5	3.3	4.3	5.7	9.7
% of Specialists SIC2	0.604	0.657	0.682	0.702	0.725	0.754	0.771	0.805	0.837	0.896
% of Specialists SIC3	0.472	0.533	0.564	0.576	0.606	0.633	0.662	0.696	0.736	0.820
Forecast Dispersion	0.524	0.520	0.406	0.380	0.364	0.269	0.213	0.220	0.158	0.112
Forecast Error	1.169	1.154	0.909	0.824	0.762	0.662	0.540	0.474	0.384	0.293
Segment Disclosure Quality	0.366	0.365	0.361	0.359	0.358	0.358	0.349	0.341	0.335	0.339
IO	0.172	0.207	0.240	0.280	0.329	0.374	0.426	0.462	0.486	0.501
Turn	4.327	4.998	6.089	7.151	8.191	9.120	10.137	11.011	11.292	10.871
RSI	0.005	0.010	0.016	0.022	0.029	0.035	0.039	0.038	0.035	0.025
MB	2.587	2.765	2.885	2.995	3.141	3.266	3.390	3.592	3.773	4.554
Loss	0.470	0.427	0.371	0.325	0.269	0.229	0.181	0.141	0.111	0.079
Amihud	11.122	6.830	3.293	1.735	0.840	0.369	0.175	0.065	0.021	0.004
# Observations	16,344	16,079	15,768	15,180	14,615	14,132	13,351	12,268	11,048	9,579

Table 2-continued

Panel A2. Conglomerates

Size	Small	2	3	4	5	6	7	8	9	Big
# Analysts	1.1	1.4	1.7	2.0	2.4	2.8	3.4	4.3	6.0	10.1
# Specialists SIC2	0.6	0.7	1.0	1.2	1.6	1.9	2.4	3.2	4.7	8.6
# Specialists SIC3	0.4	0.5	0.7	1.0	1.2	1.5	1.9	2.7	4.0	7.6
% of Specialists SIC2	0.508	0.482	0.542	0.561	0.580	0.628	0.637	0.696	0.740	0.819
% of Specialists SIC3	0.367	0.377	0.402	0.420	0.415	0.463	0.498	0.570	0.608	0.711
Forecast Dispersion	0.507	0.435	0.459	0.389	0.388	0.409	0.250	0.250	0.207	0.133
Forecast Error	1.257	1.087	1.152	0.958	0.848	0.717	0.704	0.534	0.471	0.341
Segment Disclosure Quality	0.200	0.198	0.196	0.197	0.195	0.196	0.199	0.203	0.203	0.203
IO	0.170	0.206	0.234	0.277	0.340	0.394	0.438	0.455	0.475	0.495
Turn	4.184	4.453	5.259	6.451	7.273	8.064	8.569	9.000	9.054	8.556
RSI	0.005	0.008	0.015	0.022	0.028	0.031	0.032	0.031	0.025	0.018
MB	1.981	2.157	2.106	2.373	2.234	2.242	2.195	2.415	2.616	3.221
Loss	0.466	0.348	0.332	0.283	0.222	0.199	0.168	0.142	0.114	0.083
Amihud	11.975	7.349	3.484	1.587	0.800	0.402	0.152	0.078	0.020	0.004
# Observations	2,792	3,115	3,437	4,009	4,570	5,083	5,849	6,926	8,157	9,573

Table 2-continued

Panel B. Information Environment of Single-Segment firms and Conglomerates: The Role of Size Matching

Panel B1. No Matching

	Conglo	Single	diff	t-stat
# Analysts	5.4	4.7	0.70	*(5.28)*
# Specialists (SIC2)	4.3	4.0	0.30	*(2.41)*
# Specialists (SIC3)	3.6	3.6	0.10	*(0.74)*
% of Specialists (SIC2)	0.70	0.77	-0.07	*(-12.63)*
% of Specialists (SIC3)	0.57	0.66	-0.09	*(-14.45)*
Forecast Dispersion	0.24	0.25	-0.01	*(-1.10)*
Forecast Error	0.59	0.63	-0.04	*(-1.88)*
Segment Disclosure Quality	0.20	0.35	-0.15	*(-3.60)*
IO	0.41	0.37	0.04	*(12.65)*
Turn	7.44	8.04	-0.60	*(-2.29)*
RSI	0.02	0.02	-0.00	*(-6.14)*
MB	2.17	2.85	-0.67	*(-6.21)*
Loss	0.18	0.24	-0.06	*(-4.08)*
Amihud	1.29	1.83	-0.54	*(-3.25)*

Panel B2. Size Matching

	Conglo	Single	diff	t-stat
# Analysts	5.4	6.6	-1.20	*(-7.53)*
# Specialists (SIC2)	4.3	5.8	-1.50	*(-10.01)*
# Specialists (SIC3)	3.6	5.2	-1.60	*(-11.06)*
% of Specialists (SIC2)	0.70	0.81	-0.12	*(-12.42)*
% of Specialists (SIC3)	0.57	0.71	-0.15	*(-14.46)*
Forecast Dispersion	0.24	0.18	0.06	*(3.24)*
Forecast Error	0.59	0.50	0.09	*(3.29)*
Segment Disclosure Quality	0.20	0.35	-0.15	*(-3.54)*
IO	0.41	0.41	0.00	*(0.40)*
Turn	7.44	8.87	-1.43	*(-3.99)*
RSI	0.02	0.03	-0.00	*(-9.02)*
MB	2.17	3.07	-0.89	*(-6.12)*
Loss	0.18	0.19	-0.01	*(-1.09)*
Amihud	1.29	1.18	0.11	*(2.17)*

Table 2-continued

Panel C. Impact of Innate Business Complexity on the Information Environment

log(1 + # Analysts)		Forecast Error		IO		Turn		RSI	
	1		**2**		**3**		**4**		**5**
Intercept	0.176	**Intercept**	33.777	**Intercept**	8.349	**Intercept**	-3.947	**Intercept**	1.147
	(3.46)		*(2.78)*		*(3.81)*		*(-6.78)*		*(5.13)*
Conglo	-0.073	**Conglo**	11.406	**Conglo**	-3.817	**Conglo**	-2.074	**Conglo**	-0.381
	(-4.73)		*(2.28)*		*(-4.47)*		*(-7.45)*		*(-3.04)*
GeoMulti	0.052	**GeoMulti**	4.671	**GeoMulti**	11.407	**GeoMulti**	2.719	**GeoMulti**	0.233
	(4.15)		*(1.12)*		*(15.40)*		*(11.45)*		*(1.98)*
Size	0.026	**Size**	-0.912	**Size**	0.021	**Size**	0.053	**Size**	-0.036
	(50.51)		*(-9.40)*		*(0.72)*		*(5.10)*		*(-7.41)*
MB	-0.000	**Rdsales**	0.258	**Div**	0.204	**MB**	0.043	**MB**	0.026
	(-0.56)		*(2.16)*		*(8.76)*		*(10.21)*		*(10.92)*
Beta	0.000	**Lev**	0.383	**Age**	-0.054	**Beta**	0.037	**Beta**	0.021
	(0.27)		*(5.02)*		*(-3.77)*		*(26.95)*		*(10.71)*
Nasdaq	0.093	**Intan**	-0.050	**Mom1**	0.017	**Age**	0.005	**IO**	0.034
	(6.09)		*(-0.63)*		*(5.75)*		*(1.27)*		*(12.38)*
1/P	0.001	**Vol**	0.698	**Mom4**	-0.021	**Mlev**	0.007	**Ret_{t-1}**	-0.000
	(3.65)		*(7.12)*		*(-3.95)*		*(1.76)*		*(-1.83)*
Vol	-0.001			**Prc**	0.323	**# Analysts**	0.076	**Mom**	-0.009
	(-4.64)				*(14.55)*		*(9.70)*		*(-8.24)*
Ret	-0.005			**Snp**	0.042	**Prc**	-0.021	**Prc**	0.009
	(-37.76)				*(0.03)*		*(-2.55)*		*(2.24)*
Ret_{t-1}	-0.003					**Retn**	-0.024		
	(-29.22)						*(-28.76)*		
Turn	0.006					**Retp**	0.049		
	(20.42)						*(25.94)*		

Note: Panel A of this table compares the information environment of single-segment firms and conglomerates in ten size decile groups where the same size break-points are used for both single-segment firms and conglomerates. (*Conglo*) refers to conglomerates, while (*Single*) refers to single-segment firms. Panel A.1 reports statistics for a range of information quality measures as well as a set of control variables for single-segment firms while Panel A.2 reports these statistics for conglomerates. (*# Analysts*) measures the total number of analysts covering a firm. # *Specialists SIC2 (# Specialists SIC3*) reports the number of analysts that cover five or more firms in the same industry where industry is defined using the two-digit (three-digit) SIC code. For conglomerates, specialists are defined based on the industry affiliation of the firm's main segment. *% of Specialists SIC2 (% of Specialists SIC3*) reports the percentage of analysts that cover the firm who are specialists using the two-digit (three-digit) SIC code. *Forecast Dispersion* is the standard deviation of all earnings per share (EPS) forecasts, scaled by the absolute value of mean EPS forecasts. *Forecast Error* is the absolute value of the difference between consensus earnings forecast and actual earnings, scaled by actual earnings. *Segment Disclosure Quality* is the firm's average industry-adjusted (at 2-digit SIC code levels) percentage of segment items reported at the end of the fiscal year and is calculated as described in Corporate Diversification and the Cost of Debt: The Role of Segment Disclosures by Franco, Urcan and Vasvari (2015). *IO* is the percent of institutional ownership. *Turn* measures turnover as traded dollar volume scaled by market capitalization. *RSI* is relative short interest measured by outstanding short position divided by the number of shares outstanding. *MB* is the market-to-book ratio. *Loss* is an indicator variable equal to 1 if the company incurred an operating loss in the immediate quarter. *Amihud* is Amihud's (2002) transaction costs measure. The number of firm-quarters used in the analyses is abbreviated as *# Observations*. Panel B summarizes the same statistics for single-segment firms and conglomerates while also reporting the differences for the two groups. Panel B.2 reports differences between conglomerates *Conglo* and size-matched single segment firms *Single*, while Panel B.1 reports differences without any size-matching. We report the differences between the two groups using *diff,* while t-statistics are reported below in *Italic* font and in parentheses. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. Panel C extends the analyses in Panels A and B in a regression setting where we control for firm characteristics other than size deemed important by the extant literature in the determination of analyst coverage, analyst forecast errors, institutional ownership, relative short interest as well as turnover. Geographic complexity, *GeoMulti*, is a dummy variable equal to one if the firm generates its sales from a multitude of geographic segments and zero if the firm generates all of its sales from the same geographic segment. *Size* is the logarithm of market capitalization. *MB* is the market-to-book ratio. *Beta* is the CAPM market beta in the past 60 months. *Nasdaq* is a dummy variable equal to one if the firm trades on the Nasdaq stock exchange and zero otherwise. *1/P* is one divided by the year-end stock price. *Vol* is the standard deviation of daily stock returns over the fiscal year. *Ret* is the annual stock return of the current year, and Ret_{t-1} measures the annual stock return of the previous year. *Rdsales* is the ratio of R&D expense to sales. *Lev* is the book leverage measured by total liabilities divided by total assets. *Intan* is the log of one plus the ratio of intangible assets to total assets. *Div* is the dividend payout ratio. *Age* is the firm age. *Mom1* is the cumulative return in the past three months, and *Mom4* is the cumulative return between month -4 and month -12. *Prc* is the stock price. *Snp* is the membership in the S&P500 index dummy variable. *Mlev* is the market leverage. *Retp* (*Retn*) is the positive (negative) return in the previous quarter which equals to the return if it is positive (negative), zero otherwise. *Mom* is the cumulative return between month -2 and month -12. The sample period is from January 1984 to December 2010 as we are not able to calculate analyst forecast errors prior to January 1984 due to data limitations.

Table 3
Impact of Innate Business Complexity on the Post-Earnings-Announcement Drift

	1	2	3	4	5	6	7
SUE	0.102	0.068	0.353	0.077	0.351	0.005	0.297
	(3.46)	*(2.31)*	*(3.81)*	*(2.67)*	*(3.74)*	*(0.13)*	*(3.08)*
SUE*Conglo		0.141	0.129				
		(2.73)	*(2.33)*				
SUE*Comp				0.313	0.344		
				(2.79)	*(2.58)*		
SUE*Nseg						0.069	0.066
						(2.50)	*(2.11)*
SUE*MB			-0.411		-0.469		-0.512
			(-1.05)		*(-1.13)*		*(-1.23)*
SUE*Size			0.053		0.038		0.049
			(0.70)		*(0.45)*		*(0.60)*
SUE*IO			0.000		0.001		0.003
			(0.00)		*(0.06)*		*(0.13)*
SUE*Loss			-0.160		-0.161		-0.169
			(-2.95)		*(-2.95)*		*(-3.14)*
SUE*Amihud			0.796		0.815		0.824
			(2.79)		*(2.89)*		*(2.88)*
SUE*# Analysts			-0.059		-0.048		-0.054
			(-1.77)		*(-1.33)*		*(-1.50)*
Conglo		-0.001	-0.001				
		(-0.31)	*(-0.32)*				
Comp				-0.003	-0.001		
				(-0.62)	*(-0.34)*		
Nseg						-0.001	0.000
						(-0.47)	*(-0.42)*
MB			0.018		0.019		0.018
			(1.49)		*(1.48)*		*(1.49)*
Size			0.001		0.001		0.001
			(0.53)		*(0.54)*		*(0.62)*
IO			0.002		0.002		0.002
			(1.77)		*(1.69)*		*(1.71)*
Loss			-0.011		-0.011		-0.011
			(-2.40)		*(-2.46)*		*(-2.46)*
Amihud			0.034		0.035		0.034
			(1.64)		*(1.60)*		*(1.62)*
# Analysts			0.004		0.004		0.004
			(2.44)		*(2.44)*		*(2.45)*
# Observations	113,470	113,470	113,470	113,470	113,470	113,470	113,470

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise, *SUE*, and its interaction with alternative measures of innate business complexity as well as a set of control variables that impact the magnitude of the post earnings announcement drift (PEAD). (*SUE)* measures surprise unexpected earnings as $(E_t-E_{t-4})/P_t$, where E_t is the announced earnings per share for the current quarter, E_{t-4} is the earnings per share from the same quarter of the previous year, and P_t is the share price for the current quarter. *Conglo* is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with more than one business segment. Business complexity, *Comp*, is 1-HHI, where HHI is the Herfindahl index computed using segment sales within a conglomerate: for each segment, we compute the amount of sales generated by that segment as a fraction of the total sales of the firm and add up the squared fractions to compute HHI. *Nseg* is the number of segments the firm has. Segments are counted as distinct business units if they can be assigned to different two-digit SIC industries. *MB* is the market-to-book ratio. Size (*Size*) is the log of market capitalization. *IO* is the percent of institutional ownership. *Loss* is an indicator variable equal to 1 if the company incurred an operating loss in the immediate quarter. *Amihud* is Amihud's (2002) transaction costs measure. *# Analysts* is the number of the analysts covering the firm. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

Table 4
Joint impact of innate business complexity and investor sophistication on PEAD

Joint Impact of Innate Business Complexity and Institutional Ownership on PEAD					
Institutional Ownership Quintiles	**Low**	**Quintile 2**	**Quintile 3**	**Quintile 4**	**High**
SUE	0.305	0.215	0.288	0.201	0.299
	(3.18)	*(1.66)*	*(2.69)*	*(2.51)*	*(2.07)*
SUE*Conglo	0.264	0.317	0.182	0.087	-0.031
	(2.11)	*(1.97)*	*(1.25)*	*(0.68)*	*(-0.14)*
SUE*MB	-0.223	-0.017	0.184	-0.239	-0.011
	(-0.82)	*(-0.09)*	*(0.85)*	*(-1.14)*	*(-0.04)*
SUE*Size	0.014	0.038	0.160	0.402	0.101
	(0.10)	*(0.16)*	*(0.69)*	*(2.62)*	*(0.54)*
SUE*Loss	-0.288	-0.277	-0.344	0.069	-7.566
	(-2.78)	*(-1.95)*	*(-2.39)*	*(0.32)*	*(-1.06)*
SUE*Amihud	0.389	0.245	0.179	-0.013	0.384
	(2.25)	*(2.02)*	*(1.35)*	*(-0.09)*	*(2.16)*
SUE*# Analysts	-0.115	-0.072	0.004	-0.131	-0.212
	(-1.50)	*(-0.57)*	*(0.04)*	*(-1.35)*	*(-1.56)*
Conglo	-0.002	-0.008	-0.000	0.002	0.004
	(-0.52)	*(-2.33)*	*(-0.04)*	*(0.82)*	*(1.37)*
MB	0.002	0.004	0.012	0.002	0.001
	(0.20)	*(1.90)*	*(2.49)*	*(1.21)*	*(0.76)*
Size	-0.000	0.000	0.000	-0.001	0.002
	(-0.08)	*(0.25)*	*(-0.04)*	*(-0.42)*	*(0.99)*
Loss	-0.004	-0.010	-0.009	-0.009	0.092
	(-0.73)	*(-1.56)*	*(-1.49)*	*(-1.69)*	*(0.81)*
Amihud	0.008	0.002	0.001	0.001	- 0.003
	(1.16)	*(1.17)*	*(0.90)*	*(0.30)*	*(-1.26)*
# Analysts	0.003	0.003	0.005	0.007	0.003
	(1.68)	*(1.66)*	*(3.10)*	*(3.69)*	*(1.29)*
# Observations	23,947	21,421	22,717	22,479	22,904

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise, SUE, and its interaction with innate business complexity, measured using the *Conglo* dummy, in five distinct cross-sections sorted based on the percentage owned by institutions *(IO)*. *Conglo* is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with operations in at least two distinct industries based on the SIC-2 descriptions of industry. Every quarter, firms are classified into five distinct institutional ownership groups. In column (1) we use firm-quarters with the lowest institutional ownership, in column (2) we conduct our analyses for firm-quarters where the institutional ownership is in the 2nd lowest quintile, in column (3) we limit our analyses to firm-quarters where the institutional ownership is in the median quintile, in column (4) we use firm-quarters in the 2nd highest institutional ownership quintile and in column (5) we use firm-quarters that are in the highest institutional ownership quintile. The analyses in the table also control for the interactions of SUE with market-to-book (*MB*), size measured as the logarithm of market capitalization (*Size*), a quarterly loss dummy that takes on the value of one when the firm incurs losses (*Loss*), a measure of transaction costs (*Amihud*) and the number of analysts (*# Analysts*), as well as (*Conglo*), (*MB*), (*Size*), (*Loss*), (*Amihud*) and (*# Analysts*) themselves. Detailed definitions of size *(Size)*, market-to-book ratio *(MB)*, the *(Loss)* dummy, Amihud measure (*Amihud*) and *(# Analysts)* are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in Italic font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as # Observations.

Table 5
Delayed Response Reaction for Single-segment Firms versus Conglomerates

Panel A. PEAD in Extreme Deciles			
	CAR(-1;1)	**CAR(2;60)**	**CAR(-1;60)**
SUETop	0.028	0.022	0.050
	(12.22)	*(3.67)*	*(7.70)*
SUETop*Conglo	-0.002	0.015	0.014
	(-0.66)	*(2.12)*	*(1.74)*
SUETop*MB	-0.001	-0.003	-0.004
	(-0.91)	*(-1.10)*	*(-1.34)*
SUETop*Size	-0.004	-0.001	-0.005
	(-1.49)	*(-0.15)*	*(-0.66)*
SUETop*IO	0.001	-0.006	-0.006
	(0.42)	*(-1.84)*	*(-1.56)*
SUETop*Loss	-0.005	-0.018	-0.023
	(-1.79)	*(-2.55)*	*(-3.00)*
SUETop*Amihud	0.008	0.033	0.041
	(1.47)	*(2.44)*	*(2.78)*
SUETop*# Analysts	-0.003	-0.01	-0.013
	(-2.22)	*(-2.64)*	*(-3.23)*
Conglo	0	-0.011	-0.010
	(0.10)	*(-2.10)*	*(-1.92)*
MB	0.001	-0.003	-0.002
	(1.310	*(-1.35)*	*(-0.80)*
Size	0.002	0.001	0.002
	(1.32)	*(0.15)*	*(0.60)*
IO	0.002	0.005	0.007
	(1.89)	*(2.17)*	*(2.68)*
Loss	-0.002	0.005	0.003
	(-1.40)	*(1.13)*	*(0.57)*
Amihud	-0.002	-0.003	-0.005
	(-0.46)	*(-0.35)*	*(-0.49)*
# Analysts	0.002	0.01	0.012
	(2.02)	*(4.02)*	*(4.46)*
# Observations	18,484	18,484	18,484

Panel B. Delayed Response Ratio			
	Single	**Conglo**	**Diff**
Delayed Response Ratio	0.445	0.591	0.146
	(6.36)	*(10.87)*	*(2.17)*
# Observations	18,484	18,484	

Note: Panel A of this table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the three days around earnings announcements, CAR(-1;+1) and in the post-announcement window, CAR(+2;+60), on the top decile dummy (*SUETop*) and on its interactions with the conglomerate dummy (*Conglo*), market-to-book ratio (*MB*), size (*Size*), institutional ownership (*IO*), quarterly loss dummy that takes on a value of one when the firm incurs losses (*Loss*), a measure of transaction costs (*Amihud*) and the number of analysts (*# Analysts*), as well as (*Conglo*), (*MB*), (*Size*), (*Loss*), (*Amihud*) and (*# Analysts*) themselves. SUETop is 1 for the top *SUE* decile and 0 for the bottom *SUE* decile and helps capture hedge returns to going long on the highest SUE decile and going short on the lowest SUE decile (all other firms are dropped from the sample). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. Panel B uses the results in Panel A to estimate what fraction of information in earnings announcement is incorporated into the prices outside of the earnings announcement window. Specifically we calculate the ratio of the drift return, CAR(+2,+60), to the total earnings reaction return, CAR(-1,+60), to measure the delayed response ratio for single-segment firms and conglomerates, respectively, and calculate the difference in the delayed response for these two groups of firms for extreme positive (negative) surprise earnings deciles. In Panel B, the z-statistics are reported below each coefficient in *Italic* font and in parentheses. *Conglo* is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with more than one business segment. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

Table 6
Post-Earnings-Announcement Drift and Changes in Firm Complexity

PEAD and New Conglomerates			
	1	**2**	**3**
SUE	0.069	0.069	0.069
	(3.46)	*(3.46)*	*(3.46)*
SUE*Conglo	0.103	0.116	0.091
	(2.83)	*(3.20)*	*(2.71)*
SUE*NewConglo	0.145		
	(1.90)		
SUE*M&A		0.055	
		(0.48)	
SUE*NoM&A			0.605
			(1.83)
SUE*MB	0.086	0.121	0.087
	(0.48)	*(0.64)*	*(0.48)*
SUE*Size	-0.022	-0.024	-0.021
	(-0.89)	*(-0.97)*	*(-0.86)*
Size	0.002	0.002	0.002
	(2.35)	*(2.38)*	*(2.34)*
MB	0.004	0.005	0.005
	(0.57)	*(0.57)*	*(0.58)*
Conglo	-0.003	-0.004	-0.003
	(-1.50)	*(-1.62)*	*(-1.53)*
NewConglo	-0.004	-0.002	-0.005
	(-1.62)	*(-0.65)*	*(-1.36)*
# Observations	236,976	236,976	236,976

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise (*SUE*), interactions of SUE with alternative measures of firm complexity (*Conglo* and *NSeg*), as well as the interaction of SUE with a dummy variable for newly created conglomerates (*NewConglo*). We also control for market-to-book (MB), firm size (*Size*), and their interactions in all the regressions. *NewConglo* dummy is equal to one for two years after a firm reports an increase in the number of segments and zero otherwise. NewConglo is set to zero for all single-segment firms. SUE*M&A (SUE*NoM&A) is the interaction of SUE with NewConglo for segment increases that can be attributed to diversifying M&A activity (that cannot be attributed to diversifying M&A activity). Detailed descriptions of all firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

Table 7
Impact of Dispersion in Segment Growth Rates (HTSD) on Post Earnings Announcement Drift

PEAD in the Conglomerates Only Sample		
	1	**2**
SUE	0.148	0.142
	(2.78)	*(2.55)*
SUE*HTSD	0.154	
	(1.77)	
SUE*LogHTSD		0.251
		(2.09)
SUE*MB	0.243	0.237
	(0.83)	*(0.81)*
SUE*Size	0.001	-0.007
	(0.02)	*(-0.10)*
MB	-0.004	-0.004
	(-1.04)	*(-1.02)*
Size	0.004	0.004
	(2.79)	*(2.77)*
HTSD	-0.004	
	(-2.00)	
LogHTSD		-0.009
		(-2.21)
# Observations	64,405	64,405

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise, SUE, and its interaction with *HTSD*, a theoretical construct proposed by Hirshleifer and Teoh (2003), which captures the level of dispersion in segment growth rates with respect to the aggregate growth rate of the firm. *HTSD* is the Hirshleifer and Teoh (2003) segment-growth dispersion measure computed using segment growth rates within a conglomerate: for each segment, we compute the deviation of its growth rate from the firm's aggregate growth rate and square it, we then value-weight all segment deviation squared values by the amount of sales generated by that segment as a fraction of the total sales of the firm and add up all the squared segment deviation values weighed by corresponding sales-share values to calculate *HTSD*. *LogHTSD* is the natural logarithm of one plus *HTSD*. Segments are counted as distinct business units if they can be assigned to different two-digit SIC industries. Detailed descriptions of market-to-book ratio (*MB*) and size (*Size*) are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in Italic font and in parentheses. The sample period is from January 1978 to December 2011. The one-year lag in the sample is necessary in order to calculate segment and firm growth rates. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as # Observations.

Table 8
Robustness: Controlling for Potential Spillover from Industry-wide Information Events on PEAD

Complexity Measure	Conglo	Conglo	Comp	Nseg
	1	2	3	4
SUE	0.375	0.350	0.347	0.286
	(4.03)	*(3.90)*	*(3.80)*	*(3.09)*
SUE*Complexity		0.136	0.357	0.072
		(2.45)	*(2.70)*	*(2.25)*
PCRet* Complexity	0.046	0.029	0.040	0.044
	(2.19)	*(1.29)*	*(1.85)*	*(1.97)*
SUE*MB	-0.542	-0.396	-0.455	-0.496
	(-1.31)	*(-1.02)*	*(-1.11)*	*(-1.20)*
SUE*Size	0.070	0.049	0.034	0.043
	(0.83)	*(0.63)*	*(0.39)*	*(0.52)*
SUE*IO	0.002	-0.000	0.001	0.003
	(0.07)	*(-0.02)*	*(0.04)*	*(0.12)*
SUE*Loss	-0.154	-0.160	-0.160	-0.168
	(-2.77)	*(-2.96)*	*(-2.97)*	*(-3.17)*
SUE*Amihud	0.784	0.795	0.810	0.820
	(2.71)	*(2.89)*	*(2.96)*	*(2.97)*
SUE*# Analysts	-0.049	-0.059	-0.048	-0.055
	(-1.47)	*(-1.77)*	*(-1.34)*	*(-1.51)*
Complexity		-0.001	-0.002	-0.000
		(-0.29)	*(-0.49)*	*(-0.53)*
PCRet	-0.008	-0.004	-0.007	-0.007
	(-0.37)	*(-0.17)*	*(-0.31)*	*(-0.32)*
MB	0.019	0.018	0.018	0.017
	(1.53)	*(1.57)*	*(1.55)*	*(1.55)*
Size	0.001	0.001	0.001	0.001
	(0.54)	*(0.60)*	*(0.62)*	*(0.70)*
IO	0.002	0.002	0.002	0.002
	(1.81)	*(1.85)*	*(1.79)*	*(1.80)*
Loss	-0.012	-0.012	-0.012	-0.012
	(-2.63)	*(-2.63)*	*(-2.70)*	*(-2.69)*
Amihud	0.035	0.034	0.036	0.035
	(1.60)	*(1.63)*	*(1.60)*	*(1.62)*
# Analysts	0.004	0.004	0.004	0.004
	(2.35)	*(2.40)*	*(2.39)*	*(2.40)*
# Observations	112,520	112,520	112,520	112,520

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise (*SUE*), interaction of *SUE* with *Conglo* (*Comp* / *Nseg*), interactions of (*SUE)* with the recurring control variables, as well as *Conglo* (*Comp* / *Nseg*) and the usual control variables themselves. Furthermore, we also control for the impact of industry-wide information events, estimated via pseudo-conglomerate returns (*PCRet*), in all columns. *PCRet* is calculated one month before the earnings announcement. To compute *PCRet*, we first compute equal-weighted returns to all single-segment firms in an industry (industries are defined based on the two-digit SIC codes). For a single-segment firm, *PCRet* is calculated as the return to other single-segment firms in its two-digit SIC industry. For conglomerates, industry returns for affiliated segments are weighed by the respective sales-shares of the business segments and the weighted average is referred to as *PCRet*. Innate business complexity variables are described in the description of Table 2 and in the Data Appendix. Recurring control variables include market-to-book (*MB*), size (*Size*), institutional ownership (*IO*), a quarterly loss dummy that takes on a value of one when the firm incurs losses (*Loss*), a measure of transaction costs (*Amihud*) and the number of analysts (*# Analysts*). *Conglo* is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with more than one business segment. Innate business complexity, *Comp*, is 1-HHI, where HHI is the Herfindahl index computed using segment sales within a conglomerate: for each segment, we compute the amount of sales generated by that segment as a fraction of the total sales of the firm and add up the squared fractions to compute HHI. *Nseg* is the number of distinct business segments that the firm operates in. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

Table 9
Robustness: Controlling for Alternative Explanations of PEAD

	1	2	3	4	5	6	7	8	9	10
SUE	0.086	0.087	0.098	0.056	0.063	0.056	0.190	0.094	0.118	0.193
	(3.65)	*(3.37)*	*(3.84)*	*(1.79)*	*(1.99)*	*(1.08)*	*(1.78)*	*(3.43)*	*(3.68)*	*(1.33)*
SUE*MB	0.080	-0.086	-0.077	0.000	0.009	-0.085	-0.166	-0.038	-0.023	-0.408
	(0.46)	*(-0.22)*	*(-0.20)*	*(0.00)*	*(0.10)*	*(-0.67)*	*(-1.15)*	*(-0.14)*	*(-0.07)*	*(-1.97)*
SUE*Size	-0.020	-0.022	-0.026	-0.015	-0.011	-0.082	-0.089	-0.012	-0.005	0.053
	(-0.80)	*(-0.71)*	*(-0.84)*	*(-0.34)*	*(-0.27)*	*(-1.55)*	*(-1.73)*	*(-0.50)*	*(-0.19)*	*(0.87)*
SUE*Conglo	0.102	0.073	0.079	0.095	0.091	0.193	0.189	0.103	0.094	0.248
	(3.11)	*(2.17)*	*(2.39)*	*(1.82)*	*(1.84)*	*(2.44)*	*(2.28)*	*(3.10)*	*(2.74)*	*(2.70)*
SUE*EP			0.031							0.034
			(2.57)							*(0.95)*
SUE*FOG					-0.039					-0.053
					(-1.57)					*(-1.23)*
SUE*DRESP							-0.283			-0.256
							(-1.10)			*(-1.94)*
SUE*EarnVol									-0.027	-0.025
									(-1.95)	*(-0.60)*
MB	-0.001	0.002	0.002	0.004	0.003	0.001	0.001	-0.001	-0.002	0.008
	(-0.17)	*(0.18)*	*(0.16)*	*(0.78)*	*(0.68)*	*(0.27)*	*(0.31)*	*(-0.16)*	*(-0.29)*	*(2.67)*
Size	0.003	0.003	0.003	0.003	0.003	0.004	0.003	0.003	0.003	0.003
	(2.37)	*(2.19)*	*(2.19)*	*(2.01)*	*(2.02)*	*(2.61)*	*(2.28)*	*(2.33)*	*(2.43)*	*(1.40)*
Conglo	-0.003	-0.003	-0.003	-0.004	-0.004	0.002	0.003	-0.003	-0.003	-0.002
	(-1.14)	*(-1.16)*	*(-1.16)*	*(-1.22)*	*(-1.22)*	*(0.91)*	*(1.10)*	*(-1.38)*	*(-1.29)*	*(-0.71)*
EP			0.000							-0.001
			(-0.48)							*(-1.28)*
FOG					0.001					0.002
					(1.21)					*(1.64)*
DRESP							0.010			0.013
							(2.67)			*(2.20)*
EarnVol									-0.001	0.001
									(-0.98)	*(0.54)*
# Observations	248,258	182,640	182,640	114,794	114,794	87,365	87,365	232,236	232,236	50,861

Note: This table presents the results for quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise (*SUE*), interaction of SUE with the conglomerate dummy, (*Conglo*), and the interactions of SUE with a set of control variables, as well as the conglomerate dummy and the set of control variables themselves. The control variables include market-to-book (*MB*), size (*Size*), institutional ownership (*IO*), a quarterly loss dummy that takes on a value of one when the firm incurs losses (*Loss*), a measure of transaction costs (*Amihud*), the number of analysts (*# Analysts*) and where appropriate we also control for time-varying earnings persistence (*EP*), textual complexity, analyst responsiveness (*DRESP*), and earnings volatility (*EarnVol*). Earnings Persistence (EP) is the firm-specific time-varying autocorrelation between two adjacent quarterly seasonally differenced earnings (SDE), where the autocorrelation is estimated in a two-step procedure using 14 persistence-related firm characteristics each quarter following Chen (2013). Our proxy for disclosure complexity is the Gunning FOG index calculated as in Li (2008). We got the *FOG* data from Feng Li's website, for which we are grateful. Following Zhang (2008) our measure of analyst responsiveness at the firm level is an indicator variable *DRESPj,t* which equals 1 if at least one analyst following firm j in quarter t is responsive to earnings announcements, and 0 otherwise. Ex-ante earnings volatility (*EarnVol*) is calculated following Cao and Narayanamoorthy (2012). Detailed definitions of all control variables are either in the manuscript or in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.

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Table 10
Robustness: Accounting for Non-Linearity in SUE and Using Alternative CAR Measures in PEAD Regressions

	Carhart Alphas			Winsorized SUE			SUE as Decile Rank		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Complexity Measure	**(Conglo)**	**(Comp)**	**(NSeg)**	**(Conglo)**	**(Comp)**	**(NSeg)**	**(Conglo)**	**(Comp)**	**(NSeg)**
SUE	0.401	0.404	0.361	0.759	0.762	0.630	0.031	0.032	0.023
	(3.16)	*(3.12)*	*(2.85)*	*(5.62)*	*(5.44)*	*(4.59)*	*(4.74)*	*(5.09)*	*(2.98)*
SUE* Complexity	0.129	0.338	0.060	0.194	0.490	0.127	0.013	0.023	0.008
	(2.18)	*(2.42)*	*(1.89)*	*(1.85)*	*(1.90)*	*(2.15)*	*(2.30)*	*(1.64)*	*(2.71)*
SUE*MB	-0.352	-0.414	-0.453	-1.770	-1.792	-1.840	0.011	0.010	0.010
	(-0.96)	*(-1.02)*	*(-1.14)*	*(-1.96)*	*(-1.96)*	*(-1.98)*	*(1.14)*	*(0.96)*	*(1.05)*
SUE*Size	0.088	0.067	0.072	0.023	0.018	0.022	-0.045	-0.045	-0.049
	(0.79)	*(0.55)*	*(0.62)*	*(0.26)*	*(0.19)*	*(0.24)*	*(-1.92)*	*(-1.86)*	*(-2.03)*
SUE*IO	0.006	0.005	0.007	-0.071	-0.072	-0.070	-0.015	-0.015	-0.014
	(0.23)	*(0.21)*	*(0.03)*	*(-1.74)*	*(-1.73)*	*(-1.71)*	*(-2.26)*	*(-2.24)*	*(-2.13)*
SUE*Loss	-0.146	-0.151	-0.163	-0.299	-0.299	-0.303	-0.018	-0.018	-0.018
	(-2.62)	*(-2.57)*	*(-2.77)*	*(-3.17)*	*(-3.16)*	*(-3.19)*	*(-2.82)*	*(-2.83)*	*(-2.89)*
SUE*Amihud	0.981	1.022	1.037	1.467	1.466	1.482	-0.004	-0.006	-0.006
	(2.82)	(2.95)	(2.95)	(2.97)	(2.96)	(3.03)	(-0.17)	(-0.25)	(-0.24)
SUE*# Analysts	-0.077	-0.061	-0.067	-0.196	-0.192	-0.192	-0.025	-0.025	-0.024
	(-2.28)	(-1.65)	(-1.82)	(-4.19)	(-3.97)	(-3.64)	(-2.55)	(-2.54)	(-2.44)
Complexity	-0.005	-0.010	-0.003	-0.000	-0.001	-0.000	-0.001	-0.004	-0.001
	(-2.36)	(-2.01)	(-2.72)	(-0.19)	(-0.22)	(-0.21)	(-0.53)	(-1.29)	(-0.63)
MB	0.000	0.001	0.000	0.018	0.019	0.018	0.015	0.015	0.015
	(0.07)	(0.26)	(0.02)	(1.51)	(1.51)	(1.52)	(3.20)	(3.13)	(3.17)
Size	-0.002	-0.002	-0.001	0.001	0.001	0.001	0.037	0.037	0.037
	(-1.56)	(-1.56)	(-1.27)	(0.52)	(0.51)	(0.58)	(2.96)	(3.01)	(3.03)
IO	0.001	0.001	0.001	0.002	0.002	0.002	0.005	0.005	0.005
	(1.12)	(1.02)	(1.00)	(1.68)	(1.62)	(1.63)	(1.32)	(1.24)	(1.26)
Loss	-0.008	-0.009	-0.009	-0.011	-0.011	-0.011	-0.018	-0.018	-0.010
	(-2.19)	(-2.28)	(-2.29)	(-2.29)	(-2.31)	(-2.30)	(-2.83)	(-2.83)	(-2.29)
Amihud	0.046	0.047	0.048	0.029	0.031	0.030	0.026	0.026	0.026
	(1.99)	(1.96)	(1.95)	(1.57)	(1.55)	(1.55)	(2.29)	(2.29)	(2.29)
# Analysts	0.001	0.001	0.001	0.004	0.004	0.004	0.009	0.009	0.009
	(0.50)	(0.49)	(0.51)	(2.61)	(2.60)	(2.59)	(2.02)	(1.97)	(2.00)
# Observations	113,173	113,173	113,173	113,470	113,470	113,470	113,470	113,470	113,470

Note: This table presents the results for quarterly Fama-MacBeth regressions of firm-specific Carhart alphas in the 60 trading days (one-quarter) following earnings announcements $\alpha_C(2;60)$) on earnings surprise (*SUE*), interactions of *SUE* with three different measures of innate business complexity (*Conglo*, *Comp* and *Nseg*), interactions of SUE with a recurring set of standard controls (*Size. MB, IO, Loss, Amihud, # Analysts*) as well as the controls themselves. *MB* is market-to-book ratio, *Size* is measured as the logarithm of market capitalization, *Loss* is a dummy variable that takes on a value of one when the firm incurs losses in a given quarter and zero otherwise, *Amihud* is a measure of transaction costs and *# Analysts* is the number of analysts. Detailed definitions of size (Size), market-to-book ratio (MB), the (Loss) dummy, Amihud measure (Amihud) and (# Analysts) are in the Data Appendix. Columns one to three use the baseline definition of *SUE* (winsorized at 99.5% and 0.5% percentiles), columns four to six winsorize *SUE* at 95% and 5% percentiles, columns seven to nine transform *SUE* into decile ranks. Detailed descriptions of all variables are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in *Italic* font and in parentheses. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the analyses is abbreviated as *# Observations*.