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Firm complexity and post-earnings announcement drift

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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 firm characteristics, conglomerates have relatively low institutional ownership and short interest, are covered by fewer analysts, and these analysts have less industry expertise and make larger forecast errors. Finally, we find that an increase in organizational complexity leads to larger PEAD and document that more complicated conglomerates have even greater PEAD. Our results are robust to an extensive list of alternative explanations of PEAD as well as alternative measures of firm complexity.

Keywords Organizational complexity · Post-earnings-announcement drift · Conglomerates · Complicated firms · Firm complexity and post-earnings-announcement drift

JEL classification D82 · G11 · G12 · G14 · G32 · L14 · M41

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1 Introduction

Conglomerates have more complex organizational structures and thus are more difficult to understand than single-segment firms. We study consequences of this complexity for the market's ability to interpret and incorporate earnings news. We find that conglomerates have larger post-earnings announcement drifts (PEAD) than single-segment firms.

The paper is motivated by the recent finding of Cohen and Lou (2012) that conglomerates take longer to incorporate industry-wide shocks into their prices, compared to single-segment firms. Cohen and Lou (2012) find that returns to pseudo-conglomerates, comprised of single-segment firms, predict returns to actual conglomerates one month ahead.[1]

We focus instead on how investors process firm-specific news about the conglomerate itself. The challenges faced by the investors in our setup, that is, disaggregating the earnings announcement into information about different segments, differ from the challenges investors face in the Cohen and Lou analysis, that is, aggregating industry-level news about segments to revise the valuation of the whole conglomerate. We suggest two reasons for why difficulty in understanding conglomerates can exacerbate market inefficiency: less information intermediation and less interest from sophisticated investors, compared to single-segment firms with similar firm characteristics.[2]

The literature contains evidence suggesting that analyst coverage of conglomerates is worse than that of single-segment firms, but the evidence comes from non-random samples. For example, Gilson et al. (2001) find that focus-increasing spinoffs improve analyst coverage, since all analysts gain access to disaggregated data for the parent and subsidiary firms after the breakup. Gilson et al. (2001) also find that spinoffs lead to significant improvement in analyst forecast accuracy.

It is not clear, however, if the evidence from spinoffs is generalizable to the full sample. Krishnaswami and Subramaniam (1999) find that conglomerates that choose to break up are those that are subject to the most severe information dissemination problems: the average forecast error of a conglomerate that breaks up is four times that of a similar conglomerate that does not break up.

We directly compare conglomerates to single-segment firms in the full sample and find, controlling for the known drivers of analyst coverage and forecast precision, that conglomerates, compared to otherwise similar single-segment firms, are covered by fewer analysts, and these analysts have less industry expertise and make larger forecast errors.

[1] Pseudo-conglomerates emulate real conglomerates by using information available about single-segment firms. First, Cohen and Lou (2012) calculate industry-level returns using only returns of single-segment firms operating in each industry and then compute a composite pseudo-conglomerate return assigning to each segment its industry return and taking the value-weighted average of those returns using as the weight the fraction of sales each segment generates.

[2] We estimate information intermediation via analyst following and forecast error while we use institutional ownership and relative short interest to proxy for investor sophistication.

We hypothesize that sophisticated investors tend to avoid conglomerates, since conglomerates are hard to understand.[3] We find, controlling for relevant firm characteristics, that conglomerates have lower institutional ownership and short interest than single-segment firms and attract less aggregate trading. This result is new to the literature to the best of our knowledge. The implication of this result is slower price discovery for conglomerates and therefore stronger PEAD for multi-segment firms, compared to single-segment firms. The data confirm that PEAD is indeed stronger for conglomerates: controlling for several well-known determinants of PEAD, we find in cross-sectional regressions that on average conglomerates have PEAD that is twice as strong as that for single-segment firms.

If PEAD is stronger for conglomerates, then why don't more arbitrageurs trade on this information and more analysts specialize in conglomerates? Since relatively few sophisticated arbitrageurs attempt trading in conglomerates, costs associated with such trading must be too high, that is, giving the same amount of attention to a conglomerate means incurring higher costs in terms of time and energy, compared to a single-segment firm. Although returns to trading PEAD in conglomerates far exceed the returns to trading PEAD in single-segment firms, the alpha generated from trading PEAD in conglomerates must be falling short of the cost of processing earnings-related information about conglomerates.

Next, we present three pieces of evidence that the relation between PEAD and organizational complexity is not limited to the relation between PEAD and the conglomerate status alone. We document that more complex conglomerates have significantly higher PEAD than simpler ones, suggesting that there is a continuum in the relation between PEAD and firm complexity.

First, we examine periods right after conglomerates are formed and hypothesize that new conglomerates seem more complex to investors, as investors do not have the experience of dealing with a newly formed conglomerate. Consistent with this prediction, we find that PEAD for new conglomerates is 60% larger than that of existing conglomerates and 2.5 times larger than 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. This result can be explained by the fact that it is easier to understand merger targets, as they have existed as independent companies with their independent and audited financial records, and that mergers in general receive scrutiny from media and advisors, reducing the information asymmetry surrounding them, while new lines of business created from within are less likely to be familiar to investors and are more opaque.

[3] Unsophisticated investors, on the other hand, invest for savings/liquidity reasons and do not attempt to process firm-specific information. This leads to unsophisticated investors inadvertently holding relatively more shares of conglomerates, compared to sophisticated investors who avoid investing in more difficult to understand multi-segment companies. This, however, does not imply that unsophisticated investors will improve their investment performance by picking up excess returns through trading more complicated firms that are ignored by institutions. Such investment improvement does not occur because unsophisticated investors passively hold both winners and losers, the alphas of which cancel out.

The stronger PEAD for new conglomerates also alleviates the concern that both conglomerate status and PEAD potentially relate to an omitted variable. For example, if a firm becomes a conglomerate if the omitted variable exceeds a certain threshold and a conglomerate disbands if the omitted variable drops below the threshold, then new conglomerates would have the omitted variable slightly above the threshold, while for old conglomerates it can be much higher than the threshold. If the same variable relates positively to PEAD, which would be consistent with our finding that conglomerates have higher PEAD than single-segment firms, then new conglomerates would have lower PEAD, compared to more established conglomerates, contrary to what we find. We conclude therefore that our finding that conglomerates have higher PEAD is inconsistent with the existence of an omitted variable that drives both PEAD and conglomerate status.

Second, we estimate the complexity of conglomerates by measuring the dispersion in their segment earnings growth rates. Hirshleifer and Teoh (2003) present a theoretical model that suggests that, if some investors use a conglomerate's aggregate earnings growth rate, instead of individual segments' growth rates, to extrapolate future value of the firm, the conglomerate will be mispriced. The model shows that higher dispersion in segment-level earnings growth rates will lead to higher information processing costs, which will lead to more mispricing for the conglomerate. We find, consistent with this theoretical prediction, that conglomerates with higher dispersion in their segments' growth rates have larger PEAD.

Third, we use an alternative measure of conglomerate complexity derived from segment-level differences in cost structure. Specifically, we posit that investors would have significantly more difficulty pricing conglomerates with segments that have differing cost structures. We argue that, even if investors account for different sales growth rates at the segment level, this would not be sufficient to price the conglomerate correctly without factoring in the cost structure of each segment separately. Investors would fail to correctly estimate firm-level profitability if they use firm-level operating leverage in their analyses, instead of trying to estimate profitability at the segment level using each segment's own operating leverage value. We take inspiration from the divergence in investment opportunity measure proposed by Rajan, Servaes and Zingales (2000) to estimate the divergence in the cost structure of multi-segment firms and measure the divergence in the operating leverage of multi-segment firms by calculating the standard deviation of a conglomerate's sales-weighted operating leverage divided by the equal-weighted average of operating leverage of the conglomerate's segments. We find, in line with our prediction, that conglomerates with high divergence in their segments' operating leverage have larger PEAD.

In our basic tests, we control for the impact of the loss effect (Narayanamoorthy 2006), investor sophistication (Bartov et al. 2000), liquidity (Sadka 2006), analyst coverage (Gleason and Lee 2003), and size and market-to-book.[4] Our results are further robust to

[4] 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 our main analyses to account for this. The exceptions are Tables 6 and 8, as using our usual complete set of controls would severely restrict the sample size.

a long list of alternative explanations of PEAD, such as potential spillover from the predictability documented by Cohen and Lou (2012), the impact of analyst responsiveness (Zhang 2008), the impact of earnings volatility on earnings persistence (Cao and Narayanamoorthy 2012), the time-varying nature of earnings persistence (Chen 2013), and the impact of disclosure complexity (Miller 2010; You and Zhang 2009; Feldman et al. 2010; Lehavy et al. 2011; Lee 2012) and 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.[5] Furthermore, we find no evidence that conglomerates are more likely to choose Fridays (DellaVigna and Pollet 2009) or days with more competing news (Hirshleifer et al. 2009) to announce their earnings.

Our study contributes to two strands of literature. First, we add to the literature on the determinants of PEAD. To the best of our knowledge, there is no empirical research on the relation between organizational structure and PEAD. The literature on PEAD largely focuses on the relation between PEAD and capital market characteristics, such as information uncertainty (Francis et al. 2007; Zhang 2006), investor sophistication (Bartov et al. 2000), trading frictions (Ng et al. 2008), and information production by the firm and analysts (Gleason and Lee 2003).

In terms of information production, conglomerate status (or the number of business segments) is an input-based measure, as opposed to output-based measures used by the literature, such as noisy earnings and return volatility. Hence the focus on the input-based measure can help identify the link between organizational complexity and PEAD, since earnings volatility, for example, can measure both the underlying business characteristics and actions by the manager to distort information. Likewise, return volatility can stem both from the nature of the firm's business and from the stock market state and characteristics.

Second, our paper contributes to the literature on the information environment of conglomerates. Using the full sample of all conglomerates and single-segment firms, we find that conglomerates, all else equal, have worse analyst coverage, and informed investors, such as institutions and short sellers, tend to ignore conglomerates, which is likely to lead to less market efficiency (e.g., stronger PEAD for conglomerates). To the best of our knowledge, the only paper that studies the impact of conglomeration on analyst forecasts in the full cross-section is by Thomas (2002). Thomas finds that in 1986–1995 conglomerates had larger forecast errors and larger analyst disagreement, once return volatility is controlled for. We extend Thomas's result by looking at a longer sample period and a longer list of information environment measures not limited only to analyst forecasts.

2 Hypotheses development

Cohen and Lou (2012) show that industry-level information is incorporated into conglomerates' prices with a delay, since conglomerates are harder to analyze. There could be several reasons for this. For example, analysts and investors may know the

[5] We investigate whether alternative explanations of PEAD, which could be tied to other dimensions of firm complexity, can explain our results explicitly in Tables 7, 8, 9 and 10.

fraction each business segment contributes to the total sales of the conglomerate as well as the growth rates of sales at each segment but still may find it hard to predict the impact of segment-level sales on the value of the conglomerate if some segments have high fixed costs while others have mostly variable costs. In such an instance, even if one knows the sales as well as the sales growth rates for each segment, it would be difficult to predict the impact of the sales figures on profits without understanding the internal cost structure of the conglomerate.

Further complementing the findings of Cohen and Lou (2012), Chemmanur and Liu (2011) show, in a theoretical model, that organizational complexity impedes information processing for two reasons. First, division of consolidated firms into less complex units with their own financial reports reduces analysts' and 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.[6]

Our first hypothesis is that conglomerates' organizational complexity harms analyst following and consequently information production and reduces the interest of sophisticated investors in owning and trading shares of conglomerates and thus reduces market efficiency. Since these two channels are distinct from each other in the way they affect price formation, we divide Hypothesis 1 into two subsections, as follows.

Hypothesis 1a: Holding everything else constant, conglomerates are followed by fewer analysts and have larger analyst forecast errors.
Hypothesis 1b: Holding everything else constant, conglomerates have lower institutional ownership, lower short interest, and lower turnover.

Research has demonstrated the role that corporate focus can help improve the firm's information environment. In particular, Gilson et al. (2001) attribute the improvement in analyst forecast accuracy following focus increasing spinoffs in part to increased disclosure, as all analysts gain access to disaggregated data for the parent and subsidiary firms after the breakup. While Gilson et al. (2001) conduct their analyses in a nonrandom sample of conglomerates that choose to conduct spinoffs and carveouts, we test Hypothesis 1a in the full cross-section that includes all conglomerates and single-segment firms. This is important because, as Krishnaswami and Subramaniam (1999) report, the average forecast error of a conglomerate that breaks up is four times that of a similar conglomerate that does not break up. Hence the fact that conglomerates that decide to break up improve their information environment does not necessarily imply that an average conglomerate has worse information environment than an average single-segment firm.

Hypothesis 1b also invites the question of why retail investors' ownership in conglomerates is significantly larger than their ownership in single-segment firms. For our purposes, we view individual investors as liquidity traders, who buy and sell

[6] The same argument can apply to analysts who can choose the segment of the former conglomerate to follow according to their industry expertise after the conglomerate is disbanded.

based on their need to save or tap into their savings, and as such we assume they do not attempt to forecast cash flows and gain an edge by processing information about the firms they invest in as much as institutional investors do. Hence, we propose that the relatively passive approach taken by retail investors toward stock ownership ultimately leads to them investing in the very conglomerates that institutional investors shun.

The first hypothesis predicts costlier and slower processing of information about conglomerates as well as a smaller presence of sophisticated investors in the market for conglomerates' shares. Costlier information processing and reduced information intermediation about conglomerates would then suggest that conglomerates should be priced less efficiently than single segment firms, leading to Hypothesis 2a.

Hypothesis 2a: Post-earnings announcement drift (PEAD) is larger for conglomerates.

Hypothesis 2a is in line with the findings of Cohen and Lou (2012) who also document reduced market efficiency for conglomerates. While Cohen and Lou (2012) document that prices of conglomerates take longer to incorporate industry-level shocks, our research design differs from theirs, as we study how the market processes firm-specific information about conglomerates (earning announcements) as opposed to analyzing how the investors process information about the industries the complicated firm operates in. The challenges faced by the investors in our setup, that is, disaggregating the earnings announcement into information about different segments, are unique and different from those investors face in the Cohen and Lou (2012) analysis, that is, aggregating industry-level news about segments to revise the valuation of the conglomerate.

A stronger price drift in the post-announcement window can happen both because a larger fraction of the information in the earnings announcement is processed by the market with a delay and because the earnings announcement conveys more information to the market. To investigate the source of the larger PEAD for conglomerates, we follow DellaVigna and Pollet (2009) and calculate the delayed response ratio, defined as the share of the total stock response to earnings announcements that occurs in the post-announcement window. A natural implication of Hypothesis 2a would suggest that the market responds to earnings news about conglomerates more slowly, leading to Hypothesis 2b.

Hypothesis 2b: Conglomerates have higher delayed response ratios.

Conglomerates differ by their degree of complexity. Specifically, conglomerates with segments in vastly different industries (e.g., mining and retail) are likely to be harder to analyze, compared to conglomerates with segments in similar industries (e.g., metal mining and coal mining), as it would be challenging to develop expertise in dissimilar industries. There are multiple ways through which segment-level differences can lead to higher analytical costs. Hirshleifer and Teoh (2003) suggest that the high processing costs associated with analyzing earnings growth at the segment level could lead at least some investors to focus on aggregated information, even if segment level data are available. They propose measuring conglomerate complexity and the mispricing associated with it using the standard deviation of segment growth rates. We call this measure Hirshleifer-Teoh standard deviation.

Alternatively, differences in the cost structures of disparate business segments can introduce similar analytical costs. Take the case of a conglomerate with one segment with remarkably high fixed costs and the other with highly variable costs. Even if an investor knows the exact sales figures generated by each segment, it would be exceedingly difficult to predict the impact of segment-level sales on the conglomerate's overall profits without understanding the unique cost structures of the distinct segments. Thus, an alternative approach to measuring a conglomerate's level of complexity is to estimate the divergence in the cost structures of different segments operating within the same conglomerate. We estimate this divergence with the coefficient of variation of operating leverage. Coefficient of variation of operating leverage is the standard deviation of the segment-level sales-weighted imputed operating leverage divided by the equally weighted average operating leverage of its segments.

Ultimately, segment level differences due to differences in growth rates or cost structures can complicate the analysis of conglomerates, slowing price discovery about them and leading to underreaction to earnings news. This leads to our third hypothesis.

Hypothesis 3: More complex conglomerates (those with higher Hirshleifer-Teoh standard deviations and coefficients of variation of operating leverage measures) have stronger PEAD.

Another type of conglomerate that is particularly hard to analyze is newly formed conglomerates. New conglomerates lack histories, and, in many cases (such as in the case of merger with a private company or the development of a new line of business from within), the new segment also lacks observable performance history.

In the initial years, after conglomerate formation, investors (analysts) would face significant uncertainty regarding whether conglomeration will be value enhancing through synergies between segments or value-destroying, due to a decline in business focus. This uncertainty should add an extra level of complexity compared to established conglomerates. Hence, our fourth hypothesis is as follows.

Hypothesis 4: Newly formed conglomerates have larger PEAD than established conglomerates.

If conglomerate status and the level of PEAD are both positively correlated with an omitted variable, then empirical verification of Hypothesis 4 can help in addressing this omitted variable problem. Assume the relation between the omitted variable and conglomerate status is such that a firm decides to become a conglomerate when the omitted variable in question is above a certain threshold and the conglomerate disbands if the omitted variable is below the threshold. Then new conglomerates on average would be more likely to have the omitted variable slightly above the conglomeration threshold, while established conglomerates on average would have the omitted variable further above the threshold. Under such a scenario, new conglomerates with low values of the omitted variable would have lower levels of PEAD in direct opposition to Hypothesis 4. Thus, if Hypothesis 4 holds empirically, this would suggest that investors have the greatest confusion when interpreting earnings announcements of new conglomerates, due to the significant and recent change to their organizational structure supporting the notion that an increase in organizational complexity leads to larger PEAD.

3 Data and summary statistics

We use three measures of organizational complexity. The first measure, *Conglo*, is the conglomerate dummy, equal to one if the firm is a conglomerate and zero otherwise. The firm is deemed to be a conglomerate if it has business divisions in two or more industries, according to the 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, *Comp* (organizational complexity), is a continuous variable based on sales concentration. *Comp* equals 1-HHI, where *HHI* is the sum of squared sales shares of each division, $\mathrm{HHI}=\sum_{i=1}^{N} s_i^2$, 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 one and a *Comp* measure of zero, whereas a firm with sales in many industries could achieve a *Comp* score close to one.

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 accumulated between trading day two and trading day sixty after the earnings announcement. CARs are size and book-to-market adjusted following Daniel et al. (1997). 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.[7] Since we calculate *SUE* and PEAD values following Livnat and Mendenhall (2006), 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 nonnegative 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 segment data and lasts from January 1977 to December 2010. All other variables are defined in the Data Appendix.

[7] In Panel B of Table 3, calculating SUE as the deviation from consensus analyst forecasts, we find results that are qualitatively and quantitatively consistent with our main findings.

Panel A of Table 1 reports the full distribution of *SUE*, *Comp* = 1-HHI, and the number of segments for all firms and for conglomerates only. A few numbers are particularly noteworthy. First, note that *SUE* changes by 0.139 (0.064 minus -0.075) between the 95th and the fifth 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).[8] A relatively large number of conglomerates report three segments, whereas conglomerates with four or more segments comprise less than 2.5% of the full sample (and thus less than 10% of all conglomerates). Third, the distribution of firm complexity suggests that there is a substantial 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 10^{th} complexity percentile among conglomerates, which is only 0.079. A two-segment firm, for which one of the segments accounts for 90% of sales, would have a complexity measure of 0.18. This level of complexity is comparable to the 25^{th} 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.[9]

The rest of Table 1 compares 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)). CAR (-1;1) is size and book-to-market adjusted as in Daniel et al. (1997). Panel B1 reports mean CAR values, in an attempt to assess whether conglomerates, on average, have more positive earnings surprises, and Panel B2 reports means of absolute values of CAR (-1;1), testing whether earnings surprises experienced by conglomerates differ in magnitude.

We find, in Panel B1, that *SUE*s 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 not statistically significant.

[8] 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.

[9] 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 that are not on 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.

Table 1 Descriptive statistics

Panel A1. SUE and innate business complexity distribution—All firms

			Percentiles										
	# Observations	Mean	1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	269,285	-0.004	-0.260	-0.118	-0.060	-0.028	-0.006	0.002	0.006	0.020	0.041	0.079	0.174
Nseg	269,285	1.6	1	1	1	1	1	1.2	2.0	3.1	3.6	4.2	4.7
Comp	269,285	0.108	0	0	0	0	0	0.001	0.134	0.428	0.542	0.609	0.679

Panel A2. SUE and innate business complexity distribution—Conglomerates only

			Percentiles										
	# Observations	Mean	1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	88,685	-0.004	-0.246	-0.111	-0.057	-0.027	-0.006	0.001	0.007	0.021	0.041	0.073	0.160
Nseg	88,685	2.67	2	2	2	2	2	2.2	3.1	4.0	4.4	5.0	5.7
Comp	88,685	0.351	0.007	0.016	0.036	0.076	0.190	0.365	0.499	0.604	0.661	0.699	0.741

Panel B. Earnings announcements

Panel B1. Raw Values				Panel B2. Absolute Values				Panel B3. Earnings Persistence			
	Single	Conglo	S-C		Single	Conglo	S-C		Single	Conglo	S-C
SUE	0.156%	0.155%	0.001%	SUE	0.626%	0.660%	-0.03%	Foster (1977)	0.249	0.235	0.014
	(6.86)	*(4.03)*	*(0.06)*		*(17.40)*	*(17.20)*	*(-1.52)*		*(17.52)*	*(10.32)*	*(0.76)*
EA	0.137%	0.161%	-0.024%	EA	3.575%	2.866%	0.71%	Chen (2013)	0.283	0.270	0.013
	(2.80)	*(3.17)*	*(-0.59)*		*(12.50)*	*(14.40)*	*(5.67)*		*(43.52)*	*(33.72)*	*(4.76)*

Note: This table presents mean 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. Organizational 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 $(E_t\text{-}E_{t\text{-}4})/P_t$, where E_t is the announced earnings per share for the current quarter, $E_{t\text{-}4}$ 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. Earnings persistence is calculated in two ways: first following Foster (1977) and Cao and Narayanamoorthy (2012) and second following Chen (2013). Detailed explanations of *SUE*, *Nseg*, *Comp*, *EA*, and *Earnings Persistence* are in the Data Appendix. The differences for different firm characteristics between single segment firms (Single) and conglomerates (Conglo) are calculated quarterly and the time-series averages of these differences are reported in the difference columns (S-C). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in italics and in parentheses. The sample period is from January 1977 to December 2010. The number of firm-quarters used in the analyses is abbreviated as # Observations

Panel B2 shows that the magnitude of announcement CARs is significantly smaller for conglomerates (2.866%) than for single-segment firms (3.575%), whereas the average absolute magnitude of *SUE* is similar for both groups of firms (0.626% versus 0.660%). 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 as well as reduced institutional trading, compared to single-segment firms of the same size. The smaller absolute CARs of conglomerates, coupled with similar *SUE* of conglomerates and single-segment firms, also suggest that the stronger PEAD for conglomerates is unlikely to imply that conglomerates experience more information revelation at earnings announcements.

Panel B3 is our first attempt to differentiate between our result and the result of Cao and Narayanamoorthy (2012), who find stronger PEAD for firms with low earnings volatility. (The formal horse race is in Table 8.) In their sample period, Cao and Narayanamoorthy (2012) show that autocorrelation of *SUE* changes from 0.42 to 0.31 as one goes from the bottom to the top earnings volatility quintile, suggesting that there is more persistence in the earnings surprises for firms with lower earnings volatility. This finding corroborates Bernard and Thomas' (1989) random walk fixation theory, which suggests that investors erroneously assume that earnings follow seasonal random walk and believe that there is no autocorrelation in earnings surprise values. In reality, however, there is heterogeneity in the autocorrelation in earnings surprise values: the greater the autocorrelation of *SUE* is, the larger will be the error investors make in estimating earnings, which will subsequently lead to stronger PEAD.

Since conglomerates are likely to have less volatile earnings than single-segment firms, due to both conglomerates being larger as well as due to the diversification benefits obtained through the coinsurance between segments, the difference in PEAD between conglomerates and single-segment firms may be attributable to differences in earnings persistence.

Panel B3, however, finds little support for this hypothesis. We measure earnings persistence in two ways. In the first row of Panel B3, we perform the cross-sectional regression of *SUE* on *SUE* from the previous quarter, as Foster (1977) and Cao and Narayanamoorthy (2012) do. The regression is performed separately for conglomerates and single-segment firms using Fama–MacBeth (1973) style regressions; the S-C cell tests the hypothesis if the average difference between the two time-series of slopes is zero. In the second row of Panel B3, we use the firm-level earnings persistence measure from Chen (2013) and report its median for single-segment firms, conglomerates, and the test of whether the medians are equal. In both cases, we find that the *SUE* autocorrelations for single-segment firms and conglomerates are very close to each other (0.249 versus 0.235 in the first row, 0.283 versus 0.27 in the second row) and never in favor of conglomerates, indicating to us that the difference in PEAD between conglomerates and single-segment firms cannot be explained by differences in earnings persistence.

4 Results

4.1 Information production for conglomerates and similar single-segment firms

Building on our first hypothesis that conglomerates have greater organizational 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 organizational complexity and information production about the firm by comparing single-segment firms and conglomerates across several dimensions. First, we investigate the impact of organizational complexity on the quality of information intermediation by comparing the number of analysts as well as the magnitude of their forecast errors for single-segment firms and multi-segment firms.[10] Second, we explore how organizational complexity affects ownership and trading by sophisticated investors. We associate larger institutional ownership as well as larger relative short interest with greater presence of sophisticated investors and compare the sophistication of investor clienteles in single-segment firms and multi-segment firms using these two metrics.[11] Finally, we assess the impact of organizational complexity on general investor interest by analyzing its impact on turnover.

We run panel regressions and cluster standard errors by firm-year, following Peterson (2009). The regressions control for firm size, market-to-book, CAPM beta, lagged returns, momentum returns, share price, capital structure, firm age, firm profitability, loss dummy, number of analysts, return volatility, and other firm-characteristics deemed relevant by the extant literature where necessary.[12] 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 several overseas segments and zero if the firm generates all of its sales from one 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 using it as a proxy for business complexity.[13]

[10] In unreported tables, we also investigate the impact of organizational complexity on forecast dispersion, analyst quality proxied by analysts' industry specialization as well as accounting disclosure quality using segment disclosure quality, following Franco et al. (2016). Those analyses yield results consistent with our hypotheses. Results are available upon request.

[11] Institutional ownership (relative short interest) is the number of shares held by institutions (number of shares shorted) divided by number of shares outstanding.

[12] The turnover regression uses the control variables from Chordia et al. (2007), the institutional ownership regression follows Gompers and Metrick (2001), determinants of forecast errors are from Thomas (2002), the analyst coverage regression is from Hong, Lim, and Stein (2000), and the short interest regression follows Barinov and Wu (2014).

[13] 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 the analysis of Duru and Reeb (2002) and find no evidence that international diversification reduces analyst forecast accuracy in the post-2000 period. Results are available upon request.

Table 2 Impact of organizational complexity on the information environment of the firm

log(1 + # Analysts)		Forecast Error		log(IO)		Turn		RSI	
	1		2		3		4		5
Intercept	0.008	Intercept	0.434	Intercept	-1.464	Intercept	-12.121	Intercept	-0.007
	(0.04)		*(0.66)*		*(-2.55)*		*(-7.13)*		*(0.89)*
Conglo	-0.108	Conglo	0.040	Conglo	-0.346	Conglo	-0.379	Conglo	-0.003
	(-10.73)		*(2.84)*		*(-3.46)*		*(-2.04)*		*(-4.25)*
GeoMulti	0.008	GeoMulti	-0.026	GeoMulti	-0.044	GeoMulti	-0.682	GeoMulti	-0.003
	(0.79)		*(-1.91)*		*(-0.47)*		*(-4.14)*		*(-4.41)*
Size	0.265	Size	0.000	Size	0.072	Size	0.633	Size	-0.000
	(66.38)		*(-0.04)*		*(1.52)*		*(7.06)*		*(-1.10)*
MB	0.028	MB	-0.014	MB	-0.000	MB	0.127	MB	0.001
	(21.12)		*(-7.83)*		*(-0.65)*		*(5.28)*		*(6.64)*
Beta	0.075	Rdsales	-0.034	Div	-0.040	Beta	2.604	Beta	0.008
	(12.90)		*(-5.57)*		*(-0.39)*		*(19.36)*		*(17.11)*
Nasdaq	0.041	Lev	0.318	Age	0.000	Age	-1.268	IO	0.001
	(3.54)		*(10.74)*		*(0.03)*		*(-11.22)*		*(12.68)*
1/P	-0.151	Intan	-0.273	Mom1	0.001	Mlev	2.425	Ret_{t-1}	0.000
	(-8.99)		*(-5.07)*		*(2.47)*		*(6.79)*		*(1.81)*
Vol	-0.735	Vol	1.440	Mom4	-0.001	# Analysts	1.072	Mom	-0.004
	(-8.27)		*(12.11)*		*(-3.15)*		*(10.09)*		*(-10.54)*
Ret	-0.015	Loss	0.196	Prc	0.005	Prc	2.594	Prc	0.009
	(-3.57)		*(12.41)*		*(1.78)*		*(18.24)*		*(14.52)*
Ret_{t-1}	0.011	Age	-0.004	Snp	-0.237	Retn	-0.288	Loss	0.008
	(3.31)		*(-6.27)*		*(-1.34)*		*(-58.27)*		*(13.23)*
Turn	0.107	Log(1 + #Analysts)	-0.216	Turn	0.865	Retp	0.208		
	(29.70)		*(-18.77)*		*(3.48)*		*(63.09)*		

Table 2 (continued)

log(1 + # Analysts)		Forecast Error		log(IO)		Turn		RSI	
	1		2		3		4		5
Loss	-0.087			Vol	-0.049	Loss	0.596		
	(-10.36)				*(-8.95)*		*(4.50)*		
Age	*-0.005*			Loss	-0.556				
	(-9.54)				*(-8.60)*				
ROA	0.147								
	(4.97)								
# Observations	185,380	# Observations	188,746	# Observations	133,435	# Observations	445,347	# Observations	360,053

Note: In this table, we analyze the link between organizational complexity and information production about the firm by comparing single-segment firms and conglomerates across several dimensions. In particular, we investigate the impact of organizational complexity on the quality of information intermediation and the participation of the general investor public as well as sophisticated investors in ownership and trading decisions. In doing so, we run panel regressions. We are specifically interested in five dependent variables. *# Analysts* measures the total number of analysts covering a firm. *Forecast Error* is the absolute value of the difference between consensus earnings forecast and actual earnings, scaled by actual earnings. *IO* is the percentage 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. *# Analysts* and *Forecast Error* help us measure the quality of information intermediation. *IO* and *RSI* proxy for investor sophistication. *Turn* captures the trading of the general investor public. The regressions control for a myriad of firm characteristics. *Conglo* is the conglomerate dummy, equal to one if the firm is a conglomerate and zero otherwise. Conglomerates are defined as firms with more than one business segment. Geographic complexity, *GeoMulti*, is a dummy variable equal to one if the firm generates its sales from several geographic segments and zero if the firm generates all of its sales from one 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. *Mom* is the cumulative return between month -2 and month -12. *Mom1* is the cumulative return in the past three months. *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) and zero otherwise. *Loss* is an indicator variable equal to 1 if the company incurred an operating loss in the immediate quarter. *ROA* is return on assets. In all columns, we control for year-quarter fixed effects as well as industry fixed effects and cluster standard errors by firm-year, following Peterson (2009). The number of firm-quarters used in the analyses is abbreviated as *# Observations*. The sample excludes firms with market caps in the lowest NYSE/AMEX size quintile. The sample period is from January 1984 to December 2010, as we cannot calculate analyst forecast errors prior to January 1984 due to data limitations. The t-statistics are reported below each coefficient in italics and in parentheses

We find that the coefficient on the *Conglo* dummy is negative and statistically significant in columns (1), (3), (4) and (5) while positive and statistically significant in column (2), in line with our expectations. The statistically significant and positive coefficient on *Conglo* in column (2) suggests that analysts make larger forecast errors about conglomerates, all else fixed.[14] Consistent with our Hypotheses 1a and 1b, conglomerates have lower analyst coverage, institutional ownership, relative short interest, and turnover, holding fixed other relevant firm characteristics known to affect those variables.[15]

Coefficients on *GeoMulti* suggest that it is unrelated to analyst coverage and institutional ownership and it is negatively related to analyst forecast error. Taken together, these findings suggest that geographic complexity is a poor proxy for firm complexity, supporting our use of organizational form instead. Finally, controlling for geographic complexity does not change our inferences regarding sophisticated investors' preference to avoid trading in organizationally complicated firms.

In Table 2, we find that, when compared to single-segment firms of similar characteristics, conglomerates are followed by fewer analysts and those analysts make larger forecast errors. Lower information quality production about conglomerates, compared to single-segment firms of similar characteristics, 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 complexity of operating in multiple lines of business makes conglomerates significantly harder 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: Organizational complexity leads to higher post-earnings announcement drift

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

[14] In untabulated results, we find that simply controlling for the confounding effect of size shows that conglomerates have larger forecast errors (18% higher), lower analyst coverage (1 to 2 fewer), lower turnover (1.4% less), and lower short interest (0.5% less), compared to single-segment firms of comparable size.

[15] Short interest can also reflect a directional bet, but this consideration works against our finding that short sellers avoid conglomerates, like institutions and analysts do. A long literature on the conglomerate discount, starting with the work of 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 (2019) 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 strongly indicates that organizational complexity influences sophisticated investors' trading choices.

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

We use size and market-to-book (MB) adjusted abnormal returns, following Daniel et al. (1997). Our measure of PEAD is the (positive) slope on *SUE*. Higher values of our complexity measures correspond to a higher degree of organizational complexity by construction. Thus, observing stronger PEAD for complex firms implies a positive coefficient on the interaction of *SUE* and complexity.

The literature on price momentum (e.g., Lee and Swaminathan 2000; Lesmond et al. 2004; Zhang 2006) 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 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 Panel A 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 fifth) *SUE* percentiles observed in Table 1 implies a CAR of 1.71% (0.88%) in the three months following the announcement for the average firm in the sample without controlling for any firm characteristics. The second column adds control variables and finds a smaller average PEAD of 1.18% (0.61%) per quarter.

In the third 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 3.84% (1.97%) per three months, which is almost four times what it is for single-segment firms.

The fourth column estimates the relation between PEAD and the conglomerate status controlling for market-to-book (MB), size (Size), institutional ownership (IO), loss effect (Loss), liquidity (Amihud), analyst coverage (# Analysts), the interactions of this large set of controls with *SUE*, and momentum (Mom). All control variables, except for *Loss*, are standardized to have a mean of zero and a standard deviation of one. *Loss* is a dummy variable equal to 1 if the company incurred an operating loss in the immediate quarter and zero otherwise. We find that controlling for interactions of *SUE* with additional firm characteristics slightly reduces the loading on the interaction term between *SUE* and the conglomerate dummy from 0.143 to 0.124.[16] After adding this large set of controls, we find that for an *average* conglomerate that has not incurred a loss in the immediate quarter, PEAD is 4.71% (2.41%) per three months after the earnings announcement when we use the *SUE* differential between

[16] It is interesting that the momentum control is insignificant; in untabulated results, we verified that this insignificance is due to the momentum crash of 2009. If 2009 and later years are dropped from the sample, the momentum control becomes significant but still does not impact our main result (the slope on the SUE-Conglo interaction).

the 97.5th and 2.5th *SUE* percentiles (95th and fifth SUE percentiles), as compared to 2.27% (1.16%) for single-segment firms.[17] This suggests that, even after controlling for a comprehensive list of firm characteristics associated with PEAD returns, conglomerates have PEAD that is more than twice as high as PEAD for single-segment firms.

Columns (5) and (6) repeat the analyses conducted in columns (3) and (4) and replace the conglomerate dummy with the continuous complexity measure *Comp*, 1-HHI. The results in columns (5) and (6) qualitatively resemble the results in columns (3) and (4). The magnitude of the coefficient on the product of SUE and the complexity measure, *Comp*, in column (5) suggests that, without controlling for the extensive list of control variables, PEAD for conglomerates is about twice as large as the PEAD for single segment firms: the median level of the complexity variable for conglomerates is 0.368. Thus using the slope of 0.315 in column (5) and the *SUE* spread between the 97.5th and 2.5th (95th and fifth) percentiles from Panel A1 of Table 1, 0.197 (0.101), we estimate the difference in PEAD of a representative conglomerate and a representative single-segment firm at 2.28% (1.17%).[18] After controlling for the long list of characteristics that impact PEAD in column (6), we observe that PEAD for an average conglomerate (an average single-segment firm) is 4.66% (2.21%), almost exactly as in our findings in column (4).

Columns (7) and (8) use the number of segments (with different two-digit SIC codes) as the third measure of complexity. Once again, the interaction term between *SUE* and complexity, *NSeg*, is statistically significant. In column (7), the magnitude of the coefficient on the product of *SUE* and the number of segments, *NSeg*, suggests that, without controlling for the confounding effects of other factors, PEAD for conglomerates is roughly twice as large as PEAD for single segment firms. The median conglomerate has 2.2 segments, so the slope of 0.069 on *SUE***NSeg* in column (7) would estimate the difference in PEAD of a representative conglomerate and a representative single-segment firm at 1.63% (0.84%) when the *SUE* differential between the 97.5th and 2.5th (95th and fifth) percentiles is used in the estimation. In column (8), economic significance of the interaction term is little changed after controlling for the usual list of independent variables and the interactions of these controls with *SUE*. After accounting for the effect of the controls, we estimate PEAD for an average single-segment firm (NSeg = 1) to be 2.4% for the three months following earnings announcements, while PEAD for an average conglomerate is 3.85% for the same duration, based on the SUE differential between the 97.5th and 2.5th percentiles.

To summarize, we find, in Panel A, after controlling for many confounding factors influencing PEAD, that among firms that have not incurred an operating loss in

[17] Here and henceforth in the coefficient interpretation an average conglomerate (single-segment) firm is assumed to have the values of all control variables at their averages (which is zero after standardization). *Loss* is not standardized, however, since the average firm is profitable.

[18] 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.

Table 3 Impact of organizational complexity on the post-earnings announcement drift

Panel A. Baseline results								
	1	2	3	4	5	6	7	8
SUE	0.087	0.060	0.052	0.115	0.061	0.112	-0.011	0.061
	(3.22)	*(2.51)*	*(1.86)*	*(2.86)*	*(2.36)*	*(2.69)*	*(-0.27)*	*(1.12)*
SUE*Conglo			0.143	0.124				
			(2.72)	*(2.23)*				
SUE*Comp					0.315	0.338		
					(2.78)	*(2.47)*		
SUE*NSeg							0.069	0.061
							(2.49)	*(1.95)*
SUE*MB				-0.186		-0.190		-0.197
				(-1.30)		*(-1.32)*		*(-1.39)*
SUE*Size				0.033		0.024		0.030
				(0.84)		*(0.55)*		*(0.71)*
SUE*IO				-0.005		-0.004		-0.003
				(-0.22)		*(-0.17)*		*(-0.10)*
SUE*Loss				-0.149		-0.152		-0.159
				(-2.72)		*(-2.73)*		*(-2.89)*
SUE*Amihud				0.109		0.111		0.113
				(3.05)		*(3.08)*		*(3.16)*
SUE*# Analysts				-0.060		-0.049		-0.053
				(-1.74)		*(-1.31)*		*(-1.44)*
Conglo		0.000	-0.001	-0.001				
		(-0.21)	*(-0.29)*	*(-0.37)*				
Comp					-0.003	-0.002		
					(-0.62)	*(-0.44)*		
NSeg							-0.001	0.000
							(-0.47)	*(-0.52)*
MB		0.002		0.002		0.002		0.002
		(2.27)		*(0.88)*		*(0.98)*		*(0.85)*
Size		0.000		0.000		0.001		0.001
		(0.30)		*(0.47)*		*(0.54)*		*(0.65)*
IO		0.002		0.002		0.002		0.002
		(1.41)		*(1.92)*		*(1.85)*		*(1.86)*
Loss		-0.011		-0.012		-0.012		-0.012
		(-2.37)		*(-2.61)*		*(-2.67)*		*(-2.67)*
Amihud		0.001		0.003		0.003		0.003
		(1.96)		*(2.18)*		*(2.03)*		*(2.11)*
# Analysts		0.004		0.004		0.004		0.004
		(2.59)		*(2.43)*		*(2.43)*		*(2.43)*
Mom		0.001		0.001		0.001		0.001
		(0.41)		*(0.43)*		*(0.43)*		*(0.42)*
# Observations	113,388	113,388	113,388	113,388	113,388	113,388	113,388	113,388
Panel B. SUE based on analyst forecasts								
	1	2	3	4	5	6	7	8
SUE	1.096	0.982	0.931	1.091	0.990	1.122	0.521	1.056
	(7.66)	*(6.66)*	*(5.38)*	*(3.24)*	*(6.29)*	*(3.32)*	*(1.78)*	*(1.95)*
SUE*Conglo			0.833	0.708				
			(2.55)	*(2.01)*				
SUE*Comp					1.877	1.633		

Table 3 (continued)

					(2.59)	*(1.93)*		
SUE*Nseg							0.431	0.494
							(2.42)	*(2.10)*
Conglo		0.000	0.000	0.001				
		(0.23)	*(0.07)*	*(0.28)*				
Comp					-0.003	-0.001		
					(-0.68)	*(-0.26)*		
Nseg							0.000	-0.002
							(-0.24)	*(-1.00)*
Controls	NO	YES	NO	YES	NO	YES	NO	YES
SUE*Controls	NO	NO	NO	YES	NO	YES	NO	YES
# Observations	90,303	90,303	90,303	90,303	90,303	90,303	90,303	90,303
Panel C. SUE standardized by its cross-sectional standard deviation								
	1	2	3	4	5	6	7	8
SUE	0.017	0.017	0.014	0.017	0.015	0.017	0.007	0.010
	(3.53)	*(4.03)*	*(2.80)*	*(3.93)*	*(2.86)*	*(3.86)*	*(0.94)*	*(1.72)*
SUE*Conglo			0.013	0.012				
			(1.87)	*(1.94)*				
SUE*Comp					0.035	0.033		
					(2.07)	*(2.20)*		
SUE*Nseg							0.008	0.008
							(2.31)	*(2.42)*
Conglo		0.000	-0.001	-0.001				
		(-0.14)	*(-0.58)*	*(-0.61)*				
Comp					-0.006	-0.004		
					(-1.25)	*(-1.09)*		
Nseg							-0.001	-0.001
							(-0.62)	*(-0.68)*
Controls	NO	YES	NO	YES	NO	YES	NO	YES
SUE*Controls	NO	NO	NO	YES	NO	YES	NO	YES
# Observations	113,388	113,388	113,388	113,388	113,388	113,388	113,388	113,388

Note: This table presents the results for quarterly Fama–MacBeth regressions of size and market-to-book adjusted cumulative returns in the 60 trading days following earnings announcements (CAR (2;60)) on earnings surprise, *SUE*, and its interaction with measures of innate business complexity as well as with a set of control variables. The regressions are performed every calendar quarter using the most recently computed SUE per firm. (*SUE)* measures surprise unexpected earnings as $(E_t\text{-}E_{t\text{-}4})/P_t$, where E_t is the announced earnings per share for the current quarter. $E_{t\text{-}4}$ is the earnings per share from the same quarter of the previous year. 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 zero otherwise. Conglomerates are defined as firms with business segments in more than one two-digit SIC industry. 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 with different two-digit SIC codes. Controls include *Size*, *MB*, *Mom*, *Loss*, *Amihud*, *IO*, and *#Analysts* as well as their products with *SUE* (*Mom* is not interacted with *SUE*). (*MB)* is the market-to-book ratio. (*Size*) is the log of market capitalization. (*Mom*) the cumulative return between month -2 and month -12. (*IO)* is the fraction of shares outstanding owned by institutions. (*Loss)* is an indicator variable equal to 1 if the company incurred an operating loss in the immediate quarter. (*Amihud)* is Amihud's (2002) price impact 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 *italics*. The sample period is from January 1977 to December 2010. The sample excludes firms with market cap in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the regressions is abbreviated as *# Observations* the immediate quarter, PEAD is roughly twice as large for a representative conglomerate than a representative single-segment firm.[19]

Panels B and C repeat Panel A (slopes on control variables and their interactions with *SUE* not reported to save space) with *SUE* based on analyst forecasts (Panel B) and *SUE* standardized by its cross-sectional standard deviation (Panel C). The reason for the latter exercise is that, as Fama (1976) points out in his Chapter 9, the standardization is necessary to interpret the slopes of Fama–MacBeth regression as returns to a tradable portfolio.

Comparing Panel A of Table 3 with Panels B and C, we observe that our main result goes through with all three research designs, since the interactions of *SUE* with the *Conglo* dummy in column (4), with *Comp* in column (6), and with *NSeg* in column (8) are all positive and significant. The magnitude of the slopes on the interaction terms still suggests that PEAD nearly doubles for conglomerates compared to single-segment firms; we also observe that both the *SUE* slope and the slope on the interaction terms are larger in Panel B, consistent with the literature that reports larger *SUE* slopes (larger PEAD) in regressions with analyst-based *SUE*.

The statistical significance of our results is slightly reduced both in Panels B and C, compared to Panel A. For example, the baseline analysis in Panel A has the t-statistic for the *SUE***Conglo* slope in column (4) at 2.23, while in Panel B, it is at 2.01 due to the reduction in sample size: when we require nonmissing and nonstale analyst forecast to compute analyst-based *SUE* in Panel B, we lose roughly 20% of the sample. It is encouraging, however, that the point estimates in all three panels are similar, as, in columns (3) and (4), the slope on *SUE* is comparable to the slope on the *SUE-Conglo* interaction, suggesting that PEAD of conglomerates is double that of single-segment firms.

4.3 PEAD and conglomerates in portfolio sorts

As Fama (1976) shows, coefficients from the cross-sectional regressions in Panel C of Table 3 can be interpreted as portfolio returns; yet portfolio sorts present more straightforward trading strategies based on the sorting variable. The main challenge in using portfolio sorts is the difficulty of controlling for confounding effects. In Table 4, we present quintile sorts on *SUE* for conglomerates and their size-industry

[19] In a related paper, Kang et al. (2017) investigate the impact of international diversification on PEAD. Using an international diversification measure that resembles the GeoMulti measure we use in Table 2, Kang et al. (2017) find that international diversification is associated with higher PEAD but document that this finding is confined to the period prior to SFAS 131 (that is, before 1998). In untabulated findings, we examine the time-series of the slope coefficients on the SUE*Conglo interaction term as well as on the interaction of SUE with alternative measures of firm complexity for a structural break around 1998 but do not find any evidence of this. In fact, the average slope on SUE*Conglo is at least 50% greater in the post-1998 period, though the difference lacks statistical significance largely due to sample size restrictions, since the comparison involves averages from two periods of 50–60 quarters each. This finding further suggests that the impact of organizational complexity on PEAD is distinct from the impact of geographic complexity on PEAD and that our results are not explained by the impact of geographic complexity on PEAD. This comports with our results in Table 2, as we find that GeoMulti does not affect the information environment in our sample period.

matches[20] among single-segment firms in an effort to control for the fact that conglomerates are, on average, larger and more liquid than single-segment firms.

To save space, Table 4 reports only the difference between returns of single-segment firms and conglomerates: for example, the upper left corner of Panel A reports the difference between CAR (2,60) of bottom SUE-quintile of conglomerates and CAR (2,60) of bottom SUE quintile of single-segment firms. (The SUE sorts are performed separately for single-segment firms and conglomerates.) The rightmost column (named H–L) reports the PEAD differential between single-segment firms and conglomerates. The top row of Panel A uses CAR (2,60) based on Daniel et al. (1997)-adjusted returns, just like Table 3 and other tables in the paper do. The next rows define CARs as alpha plus residuals from Fama and French (1993) three-factor model, the Carhart (1997) model, or the six-factor model from Fama and French (2018) that adds to the Carhart model the two new Fama–French factors, investment factor, CMA (conservative minus aggressive), and profitability factor, RMW (robust minus weak). The factor betas are calculated from firm-level regressions in the 36 months before the earnings announcement; the rows are named according to the model used to calculate CARs.

We find that conglomerates have 79–95 basis points (bp) per quarter larger PEAD than matching single-segment firms; the difference is somewhat smaller than the one implied by Fama–MacBeth regressions, because our controls are just size and industry rather than the thorough list of controls in Table 3.

Portfolio sorts additionally reveal that the difference in PEAD is solely attributable to the short side: loser conglomerates have 92–125 bp per quarter lower CARs than single-segment losers, and the t-statistics for this difference range between 2.48 and 3.54.

The reason the difference in PEAD between single-segment firms and conglomerates seems to be exclusively attributable to the short side is that, as Panel A shows, conglomerates on average have lower returns than single-segment firms in almost all cases.[21] Barinov (2019) further elaborates on the reasons for that and presents more detailed evidence.[22] Since conglomerates have lower returns in general, returns to low-SUE conglomerates will be particularly low and very different from returns to single-segment firms with low-SUE, while returns to high-SUE conglomerates will be suppressed and may turn out to be no different than returns to single-segment firms with high-SUE, which is exactly what we observe in the third row of Panel A.

[20] Single-segment firms are matched to a conglomerate of the same size and with the same two-digit SIC code of the largest segment.

[21] One can also notice that Carhart and six-factor CARs are uniformly more positive than Daniel et al. (1997) CARs, to the extent that for size-industry matches six-factor CARs are positive in all SUE quintiles. This positive bias in the Carhart and six-factor CARs is likely introduced by the presence of the size effect, which is more efficiently removed by Daniel et al. (1997) adjustment.

[22] Briefly, conglomerates are high-uncertainty firms, because, relative to similar single-segment firms, they are covered by fewer analysts, are ignored by institutions and other informed investors (see Table 2), and the high uncertainty coupled with short-sale constraints creates overpricing. As Miller (1977) suggests, short-sale constraints limit the ability of pessimists to impact the prices, and the price becomes equal to the average valuation of optimists, which increases in disagreement.

Figures 1 and 2 present the portfolio analysis in event time by depicting Carhart CARs of the top and bottom SUE quintiles for conglomerates and their size-industry and size-Loss-Amihud matches.[23] The CARs start at t = 0 (the announcement day) in Fig. 1 and at t = 2 in Fig. 2 and go until the post-announcement day marked on the horizontal axis. Similar to what we find in Table 4, we observe that the difference in PEAD between conglomerates and matching single-segment firms comes exclusively from the short side, and the main difference is accumulated in weeks two to five post-announcement, though the spread in CARs between winners and losers keeps widening until the very end of the 60-trading-days period.

Panel B studies a version of PEAD that is closer to what arbitrageurs may be implementing: in Panel B, we rebalance SUE portfolios monthly and hold stocks for two months to exclude the effects of the upcoming earnings announcement on returns. For example, if a stock posts a high *SUE* at its April 10th earnings announcement, the stock will join our top SUE portfolio for May and June. Constructing SUE portfolios this way excludes the early post-announcement period and the days preceding the next announcement but allows the arbitrageur not to clock every single announcement and not to trade every day.[24] An additional benefit of this approach is that it allows us to observe monthly returns to SUE portfolios, which increases the frequency of observations and helps us avoid estimating factor loadings and alphas at the firm level, leading to more precise estimates.

Panel B indeed produces more statistically significant estimates of the difference in PEAD between single-segment firms and conglomerates in the rightmost column. While in Panel A the difference in returns, between the portfolio that goes long on conglomerates and short on single segment firms in the highest SUE quintile and the portfolio that goes long on conglomerates and short on single segment firms in the lowest SUE quintile, is often marginally significant, in Panel B, all t-statistics for the difference exceed 2.4. The difference is also economically larger in Panel B: returns in Panel A are quarterly, with the difference in PEAD ranging from 79 to 95 bp per quarter, while in Panel B, the returns are monthly and the difference ranges from 58 to 64 bp per month. This larger difference is consistent with Figs. 1 and 2 that record that the main difference between PEAD of single-segment firms and conglomerates accumulates between week two and week five post-announcement. (Panel B, on average, drops the first two and the last two post-announcement weeks due to monthly rebalancing.)

Panel C tries to keep the whole announcement window in play while maintaining monthly return frequency; to this end, we calculate daily returns to SUE portfolios and then cumulate them to monthly returns at the portfolio level. For example, if a firm announces on January 10, April 10, and July 10, and its April 10 SUE places it in quintile five, while the other two SUEs place it in quintile three, the firm's daily returns will be part of quintile three return before April 9 and after July 11 and part

[23] Size-Loss-Amihud matching matches single-segment firms to a respective conglomerate with the same value of the Loss dummy, with similar size (picking a single-segment firm that is the closest to the respective conglomerate in terms of market capitalization), and with a similar Amihud (2002) price impact measure (between 70 and 130% of the Amihud measure of the single-segment firm).

[24] This version of PEAD is close to a short-term version of earnings momentum.

Table 4 Portfolio sorts: Difference in risk-adjusted returns between conglomerates and single-segment firms matched on size and industry

Panel A. CAR (2,60), Quarterly rebalancing						
	Low	SUE2	SUE3	SUE4	High	H–L
Daniel et al. (1997)	-1.088	-0.368	0.174	-0.410	-0.222	0.866
t-stat	*(-3.02)*	*(-1.32)*	*(0.68)*	*(-1.52)*	*(-0.71)*	*(1.99)*
FF3	-1.250	-0.486	0.029	-0.305	-0.304	0.947
t-stat	*(-3.54)*	*(-1.60)*	*(0.12)*	*(-1.12)*	*(-0.88)*	*(2.10)*
Carhart	-0.921	-0.357	0.325	-0.155	-0.096	0.824
t-stat	*(-2.48)*	*(-1.19)*	*(1.30)*	*(-0.58)*	*(-0.30)*	*(1.75)*
FF6	*-1.042*	*-0.626*	*0.096*	*-0.364*	*-0.252*	*0.789*
t-stat	(-2.65)	(-1.96)	(0.38)	(-1.42)	(-0.80)	(1.60)
Panel B. Two full months post-earnings-announcement, Monthly rebalancing						
	Low	SUE2	SUE3	SUE4	High	H–L
Daniel et al. (1997)	-0.345	0.034	0.122	0.006	0.243	0.588
t-stat	*(-2.04)*	*(0.24)*	*(1.13)*	*(0.04)*	*(1.77)*	*(2.64)*
FF3	-0.388	-0.020	0.121	-0.077	0.188	0.577
t-stat	*(-2.26)*	*(-0.14)*	*(1.09)*	*(-0.57)*	*(1.32)*	*(2.43)*
Carhart	-0.456	0.012	0.073	-0.095	0.186	0.643
t-stat	*(-2.50)*	*(0.08)*	*(0.60)*	*(-0.73)*	*(1.21)*	*(2.46)*
FF6	-0.526	-0.109	-0.011	-0.225	0.112	0.638
t-stat	*(-2.92)*	*(-0.69)*	*(-0.09)*	*(-1.69)*	*(0.77)*	*(2.55)*
Panel C. CAR (2,60), Daily rebalancing, Monthly returns						
	Low	SUE2	SUE3	SUE4	High	H–L
Daniel et al. (1997)	-0.318	-0.173	0.135	-0.179	0.038	0.356
t-stat	*(-2.41)*	*(-1.38)*	*(1.39)*	*(-1.51)*	*(0.35)*	*(2.03)*
FF3	-0.435	-0.208	0.124	-0.229	-0.023	0.412
t-stat	*(-3.16)*	*(-1.60)*	*(1.24)*	*(-1.88)*	*(-0.21)*	*(2.34)*
Carhart	-0.514	-0.220	0.120	-0.239	-0.068	0.446
t-stat	*(-3.59)*	*(-1.65)*	*(1.18)*	*(-1.94)*	*(-0.64)*	*(2.45)*
FF6	-0.549	-0.331	0.099	-0.290	-0.092	0.458
t-stat	*(-4.17)*	*(-2.42)*	*(0.93)*	*(-2.35)*	*(-0.80)*	*(2.52)*

Note: The table presents differences in risk-adjusted returns between conglomerates and single-segment firms matched to conglomerates on size and industry. Size-industry matching picks a single-segment firm from the same two-digit SIC industry as the respective conglomerate (conglomerate's industry is defined based on its largest segment in terms of sales) and requires the single-segment firm to be the closest to the conglomerate in terms of market capitalization. Risk-adjustment includes deducting from firm returns average return of firms in the same size and market-to-book deciles (Daniel et al. (1997)-adjusted returns) or estimating the alpha from the three-factor Fama and French (1993) model (FF3), the Carhart (1997) model (includes the momentum factor, MOM, in addition to MKT, SMB, and HML), or the six-factor Fama and French (2018) model (FF6, includes CMA, RMW, and MOM factors in addition to MKT, SMB, and HML)

In Panel A, standard CAR (2,60), cumulative daily returns in the 60 trading days following earnings announcements, are computed for each firm and then averaged at the portfolio level. In the FF3/Carhart/FF6 rows of Panel A, the factor models are fitted to each firm's monthly returns in the 36 months before the announcement. Then the pre-estimated slopes are used to compute the daily abnormal returns (alpha plus residuals) in the post-announcement (2,60) window

Table 4 (continued)

In Panel B, firms are held for two full calendar months post-announcement (e.g., for April earnings announcements, we keep only May and June returns), their returns are averaged into portfolio returns, and the risk-adjustment then happens at the portfolio level: in the FF3/Carhart/FF6 rows of Panel B, the differences in SUE quintile returns between conglomerates and single-segment firms are regressed on the asset-pricing factors using one full-sample regression. Portfolios in Panel B are rebalanced at the end of each month based on SUE breakpoints from earnings announcements in the preceding three months; borderline firms can switch SUE quintiles in between earnings announcements

In Panel C, firms are held for the full (2,60) post-announcement windows, their daily returns are averaged into daily returns to SUE quintiles, and then the daily returns to the quintile portfolios are cumulated to monthly returns. As in Panel B, the risk-adjustment then happens at the portfolio level: in the FF3/Carhart/FF6 rows of Panel B, the differences in SUE quintile returns between conglomerates and single-segment firms are regressed on the asset-pricing factors using one full-sample regression. Portfolios in Panel C are also rebalanced at the end of each month based on SUE breakpoints from earnings announcements in the preceding three months; borderline firms can switch SUE quintiles in between earnings announcements. In Panel C, firms also can switch SUE quintiles mid-month if an earnings announcement happens

H–L in the last column of each panel estimates the difference in PEAD between conglomerates and matching single-segment firms. The sample period is from January 1977 to December 2010. The sample excludes firms with market cap in the lowest NYSE/AMEX size quintile. The number of firm-quarters used in the regressions is abbreviated as # Observations. The t-statistics are reported below each coefficient in italics

of quintile five return between April 12 and July 9, with the announcement window not included in any quintile.

Panel C reports the PEAD differential between single-segment firms and conglomerates at 36–46 bp per month, close to what Panel A finds but with higher statistical significance due to the utilization of monthly returns: the t-statistics for the difference in returns in Panel C are always above 2, and in three cases out of four, it is in a relatively tight 2.34–2.52 range.

Finally, in Figs. 3 and 4, we try to quantify in dollar terms, the differences in the impact of PEAD for single segment firms and conglomerates, using cumulative value-weighted and equal-weighted returns, respectively. In particular, we assume that a trader initially allocates $100,000 dedicated to either strategy. Over our sample period, the initial investment of $100,000 grows to roughly $450,000 if the PEAD strategy is followed for single-segment firms versus roughly $2.3 million if the PEAD strategy is followed for conglomerates, assuming that the strategy splits the funds equally between winner (long) and loser (short) stocks.

We also observe that the difference in PEAD between conglomerates and single-segment firms was weaker in the 1980s, when our sample started, and was particularly large in 1990s, with PEAD of conglomerates staying at the same level as in 1980s and continuing to add to cumulative returns and with PEAD of single-segment firms declining.[25] This pattern is consistent with our main hypothesis that stronger PEAD for conglomerates is due to costlier processing of information about them: arbitrageurs seem to have started with arbitraging away the PEAD of

[25] In untabulated results, we perform subsample analysis of returns to PEAD strategies and find no change in PEAD of conglomerates from 1980s to later years and an economically significant decline of equal-weighted PEAD of single-segment firms.

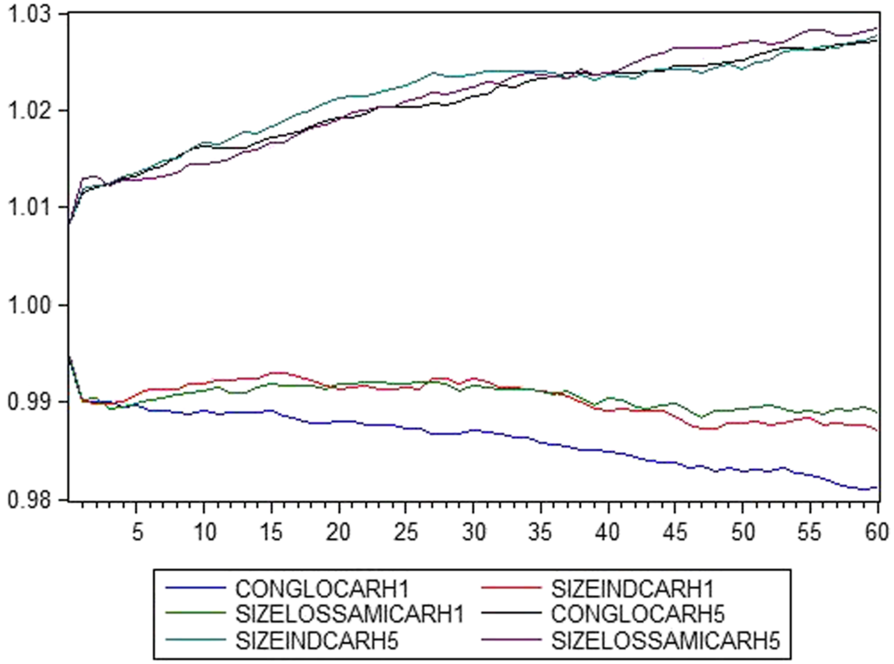

Fig. 1 Carhart CAR (0,N) for conglomerates and matching single-segment firms, Quintile 5 versus Quintile 1. *Note to Figs. 1 and 2*: The figures plot Carhart CARs of the top and bottom SUE quintiles for conglomerates and their size-industry and size-Loss-Amihud matched single-segment counterparts. The CARs start at t = 0 (the announcement day) in Fig. 1 and at t = 2 in Fig. 2 and go until the post-announcement day N marked on the horizontal axis. The Carhart (1997) model is fitted to each firm's returns using monthly returns in the 36 months before the announcement. Then the pre-estimated slopes are used to compute the abnormal returns (alpha plus residuals) in the post-announcement window (0,N) or (2,N). SizeInd matching picks a single-segment firm from the same two-digit SIC industry as the respective conglomerate (conglomerate's industry is defined based on its largest segment in terms of sales) and requires the single-segment firm to be the closest to the conglomerate in terms of market capitalization. SizeLossAmi matches single-segment firms to the respective conglomerate on the Loss dummy, size (picking a single-segment firm that is the closest to the respective conglomerate in terms of market capitalization), and the Amihud (2002) price impact measure (requiring the Amihud measure of the single-segment match to be between 70 and 130% of the Amihud measure of the respective conglomerate). CONGLOCARH1(5) depicts the PEAD for the lowest (highest) SUE quintile conglomerate portfolio. SIZEINDCARH1(5) depicts PEAD for the lowest(highest) SUE quintile single-segment portfolio that is matched to the corresponding conglomerates based on size and industry. SIZELOSSAMICARH1(5) depicts PEAD for the lowest(highest) SUE quintile single-segment portfolio that is matched to the corresponding conglomerates based on size, loss dummy, and the Amihud measure

single-segment firms in the post-1990 sample but have largely been unable to reduce PEAD for conglomerates, likely due to their reluctance to trade these more difficult-to-understand and hence costlier-to-trade securities.

According to Figs. 3 and 4, the PEAD strategy for conglomerates crashed around 2009, when momentum returns also famously crashed, while the PEAD strategy for single-segment firms did not suffer a similar fate. The crash is stronger in

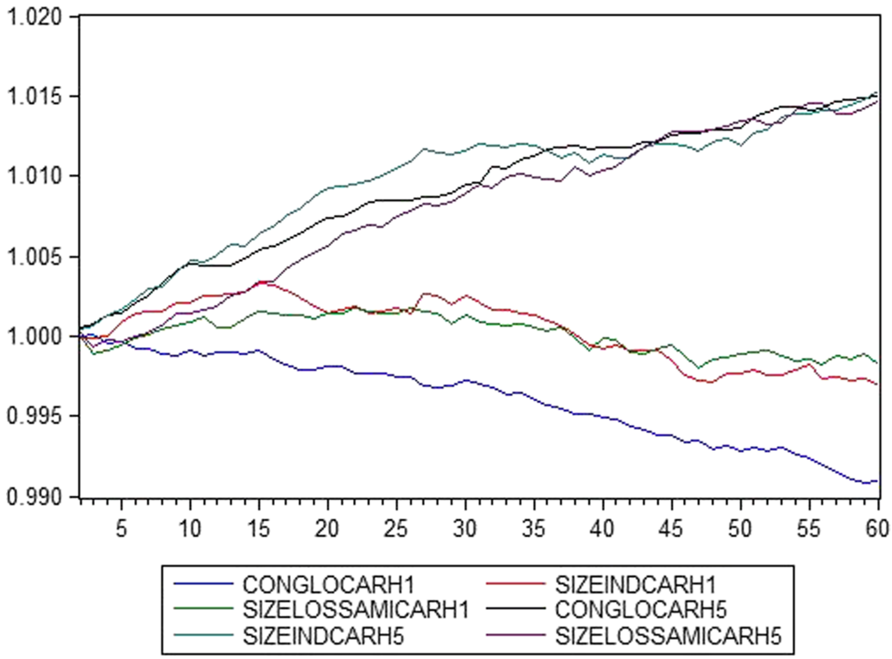

Fig. 2 Carhart CAR (2,N) for conglomerates and matching single-segment firms, Quintile 5 versus Quintile 1

value-weighted returns, suggesting that it may be driven by several huge companies (for example, sellers/producers of durable goods with a financing arm).[26]

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. Alternatively, for the same level of earnings surprise, more information may be revealed to the market on the announcement day of firms that are organizationally more complicated. 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 organizational 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 organizational complexity would both yield a positive coefficient.

[26] Another reason why the crash is stronger in value-weighted returns is that the market beta of the winners-minus-losers PEAD strategy for conglomerates is -0.25 in value-weighted returns and -0.06 in equal-weighted returns, helping the strategy in the falling market of 2008 but hurting it in the growing market of 2009. The PEAD strategy for single-segment firms has a slightly positive market beta.

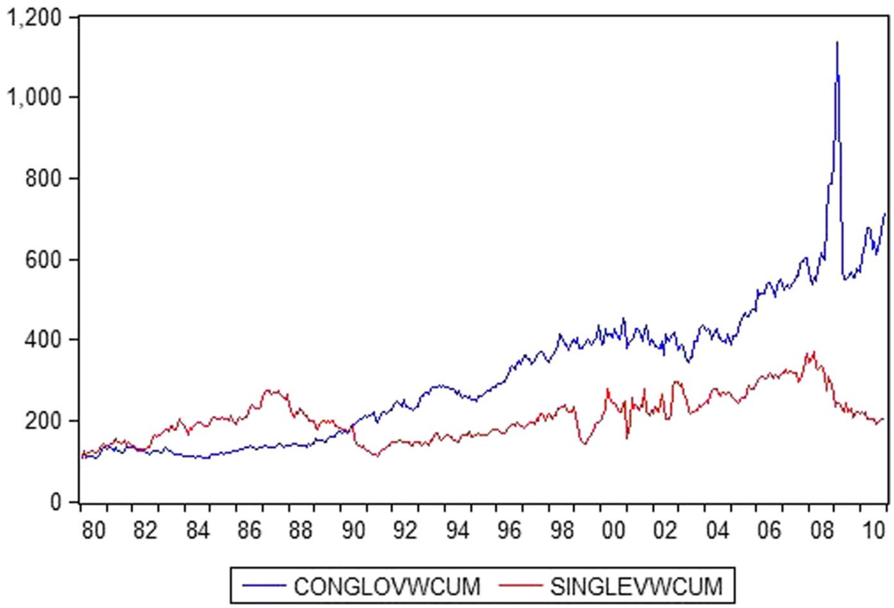

Fig. 3 Cumulative value-weighted returns to the "Quintile 5 – Quintile 1" PEAD trading strategy for conglomerates and their size-industry matches among single-segment firms (Wealth = 100 at the Sample Start). *Note to Figs. 3 and 4*: The figures plot cumulative returns to the winners-minus-losers (quintile 5 minus quintile 1 from SUE sorts) trading strategy, with initial wealth at the start of the sample being set to 100. The returns are from the SUE sorts used in Panel C of Table 4: SUE portfolios are rebalanced monthly, with firms entering the portfolios two days after earnings announcement and leaving the day before the next earnings announcement. We compute daily returns to SUE quintiles allowing firms to enter and exit SUE portfolios mid-month; borderline firms can also exit the SUE quintile they were initially assigned to (and join the neighboring quintile) when monthly rebalancing is done at the end of each month if their SUE no longer meets the updated SUE breakpoints based on all earnings announcements in the past three calendar months. The daily returns are then cumulated to monthly frequency, at which frequency risk-adjustment is performed. The cumulative returns plotted in Figs. 3 and 4 are cumulated monthly risk-adjusted returns. Weighting of firms in portfolios is performed at the stage of forming their daily returns (with value-weighting updating the weights at each portfolio rebalancing date)

In Panel A of Table 5, we perform OLS regressions of announcement returns (CAR (-1;1)), PEAD returns (CAR (2;60)), and total earnings reaction returns (CAR (-1;60)) on the top earnings surprise decile 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 and the momentum (Mom) control. Following our approach in Table 3, we exclude microcaps from the sample. *SUE-Top* is 1 (0) for the top (bottom) SUE decile and helps us capture hedge returns to going long in the highest SUE decile and going short in the lowest SUE decile.[27]

[27] As in the work of 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 10–1 SUE hedge decile return spread in returns.

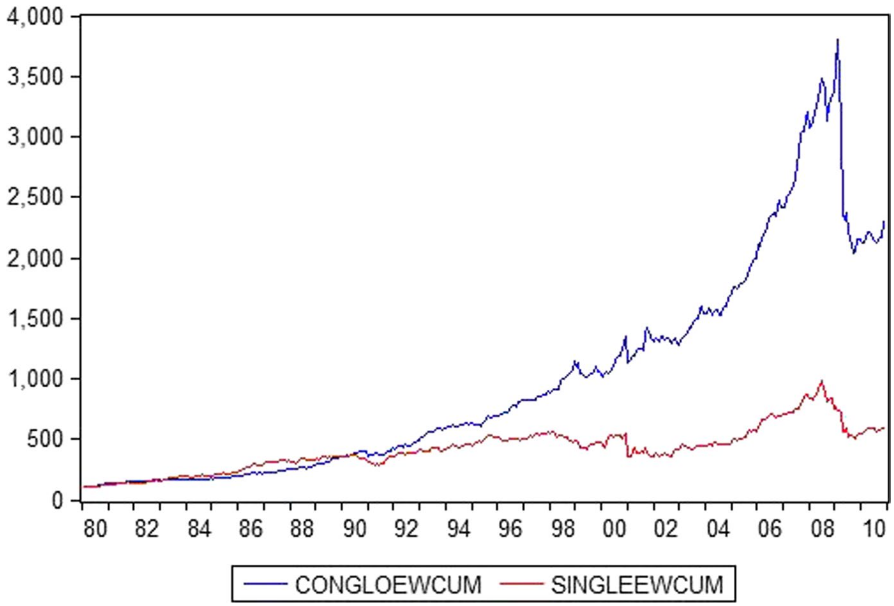

Fig. 4 Cumulative equal-weighted returns to the "Quintile 5 – Quintile 1" PEAD trading strategy for conglomerates and their size-industry matches among single-segment firms (Wealth = 100 at the sample start)

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 -0.49). This finding indicates that single-segment firms and conglomerates have similar 10–1 hedge returns in the three days around earnings announcements. On the other hand, column (2) clearly indicates, consistent with Table 4, that the 10–1 hedge strategy of going long/short on the highest/lowest SUE decile would net larger returns for conglomerates than single-segment firms as the interaction of *SUETop* and *Conglo* is economically (1.4% per quarter) and statistically significant (t-stat of 1.97). The coefficient on the interaction of *SUETop* with *Conglo* is comparable in economic magnitude to the coefficient on *SUETop* itself, 0.018 versus 0.014. Finally, column (3) shows that overall stock return responses in announcement plus post-announcement periods are significantly greater for conglomerates compared to single-segment firms. Taken together, results in Panel A of Table 5 suggest that, while conglomerates see more information revealed at earnings announcements (see the total response result in column 3), the incorporation of all extra information is delayed till the post-announcement period (see equal announcement effects in column 1), that is, stronger PEAD for conglomerates is due to delayed reaction.[28]

[28] This evidence is consistent with what is depicted in Fig. 1, which graphs CARs of extreme SUE quintile portfolios in event time. Figure 1 finds that there is minor difference between CARs of conglomerates and matching single-segment firms in the first few days after the announcement, and the gap between CARs starts to emerge around day five.

Table 5 Delayed response reaction for single-segment firms versus conglomerates

Panel A. PEAD in extreme deciles			
	Announcement returns	PEAD returns	Total earnings reaction
	CAR (-1;1)	CAR (2;60)	CAR (-1;60)
SUETop	0.023	0.018	0.041
	(11.36)	*(3.43)*	*(7.17)*
SUETop*Conglo	-0.001	0.014	0.013
	(-0.49)	*(1.97)*	*(1.66)*
SUETop*MB	-0.002	-0.003	-0.005
	(-1.34)	*(-1.02)*	*(-1.42)*
SUETop*Size	-0.004	-0.002	-0.005
	(-1.26)	*(-0.24)*	*(-0.67)*
SUETop*IO	0.001	-0.006	-0.006
	(0.47)	*(-1.80)*	*(-1.51)*
SUETop*Loss	-0.004	-0.019	-0.022
	(-1.35)	*(-2.62)*	*(-2.91)*
SUETop*Amihud	0.004	0.021	0.024
	(1.31)	*(2.88)*	*(3.14)*
SUETop*# Analysts	-0.003	-0.010	-0.013
	(-2.18)	*(-2.46)*	*(-3.05)*
Conglo	0.000	-0.010	-0.011
	(-0.11)	*(-2.05)*	*(-1.95)*
MB	0.001	-0.003	-0.002
	(1.31)	*(-1.56)*	*(-1.00)*
Size	0.002	0.002	0.003
	(0.95)	*(0.40)*	*(0.70)*
IO	0.002	0.005	0.006
	(1.96)	*(1.97)*	*(2.52)*
Loss	-0.002	0.004	0.003
	(-0.88)	*(0.92)*	*(0.55)*
Amihud	0.001	-0.008	-0.007
	(0.35)	*(-1.51)*	*(-1.29)*
# Analysts	0.002	0.010	0.012
	(2.14)	*(3.71)*	*(4.20)*
Mom	0.005	-0.006	-0.001
	(6.47)	*(-2.93)*	*(-0.47)*
# Observations	18,484	18,484	18,484
Panel B. Delayed response ratio			
	Single	Conglo	Diff
Delayed response ratio	0.446	0.605	0.159
	(5.94)	*(10.9)*	*(1.96)*
# Observations	18,449	18,449	

Note: Panel A of this table presents the results for quarterly Fama–MacBeth regressions of size- and market-to-book-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

Table 5 (continued)

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. One more control that is not interacted with *SUE* is momentum (*Mom*). The regressions are performed every calendar quarter using the most recently computed SUE per firm. SUETop is one for the top *SUE* decile and zero 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 italics 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 italics and in parentheses. *Conglo* is the conglomerate dummy, equal to 1 if the firm is a conglomerate and zero otherwise. Conglomerates are defined as firms with business segments in two or more industries with different two-digit SIC codes. 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*

Next, following DellaVigna and Pollet (2009), we quantify the magnitude of the earnings surprise underreaction for conglomerates. In particular, 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 using regression coefficients estimated in Panel A. For single segment firms, we calculate the delayed response ratio by dividing the coefficient on *SUETop* (0.018) in column (2) by the coefficient on *SUETop* (0.041) in column (3), while the delayed response ratio of conglomerates is the ratio of the sum of coefficients on *SUETop* (0.018) and *SUETop*Conglo* (0.014) in column (2) scaled by the sum of coefficients on *SUETop* (0.041) and *SUETop*Conglo* (0.013) in column (3). We report the delayed response ratios in Panel B. Standard errors are calculated using the Delta method.

Finally, we calculate the difference in the delayed response ratios for single-segment firms and conglomerates for the 10–1 hedge portfolio that trades in extreme positive (negative) surprise earnings deciles. We find that the delayed response ratio for this hedge trade is 60.5% (44.6%) for conglomerates (single-segment firms) and the difference is marginally significant with a t-statistic of 1.96. Overall Table 5 lends further support to our central hypothesis that investors have more difficulty processing earnings-related information regarding conglomerates and that information processing takes more time for complex firms.

4.5 Impact of changes to organizational form on PEAD

Conglomerates on average are significantly larger than single-segment firms and thus have lower limits to arbitrage, so the stronger PEAD for conglomerates is unlikely to pick up the well-known relation between PEAD and limits to arbitrage (e.g., Bartov et al. 2000; Mendenhall 2004). Nevertheless, it is possible that organizational complexity, conglomerate status in particular, may still relate to a certain unknown variable that in turn affects the strength of PEAD.[29]

To understand whether investors indeed have difficulty interpreting information related to more complicated firms, we focus on periods during which organizational complexity increases. If the level of organizational complexity (conglomerate status) relates to a certain unknown variable that also drives PEAD, then new conglomerates would have little exposure to this variable, and one would expect new conglomerates to have lower levels of PEAD, compared to more established conglomerates. Indeed, if firms become conglomerates once this unknown variable exceeds a certain threshold (and conglomerates disband after the same unknown variable dips under the threshold), new conglomerates would have values for this unobserved characteristic higher than but close to the threshold, while old conglomerates could have the unobserved variable at values significantly above the threshold. 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.[30]

In Panel A of 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 one. Thus, new conglomerates comprise 2.5%–4% of our sample and 10%–15% of all conglomerates.

The first column of Panel A presents results comparable to our baseline regression from column (3) of Table 3 (post-announcement CAR on *SUE*, the *Conglo dummy*, *MB*, *Mom*, *Size*, *IO*, *Loss*, *Amihud* and the interactions of *SUE* with *Conglo*, and all of the control variables except for *Mom*) with the *NewConglo* dummy and

[29] Conglomerates are on average larger, less volatile, and more transparent, and as such they are expected to have lower limits to arbitrage. Further cementing this idea, we find, in untabulated results, that, according to several measures of liquidity, including the Gibbs measure (Hasbrouck, 2009), the Roll (1984) measure, the effective spread estimate of Corwin and Schultz (2012), the Amihud (2002) measure, and the frequency of no-trade days from Lesmond et al. (1999), conglomerates on average are significantly more liquid than single-segment firms. Results are available upon request.

[30] We argue that changes to the unobserved characteristic are associated with organizational structure, i.e., when the unobserved characteristic exceeds a certain threshold, the firm becomes a conglomerate. Conglomeration is not the cause of the change in this unobserved characteristic but rather the change in the unobserved characteristic itself leads to conglomeration. There could be a different omitted variable, separate from the one we consider, such that it can increase in response to conglomeration and then subside. If such an alternative omitted variable is also associated with higher PEAD, then PEAD would be stronger for new conglomerates. We argue in this paper that this potential alternative omitted variable is organizational complexity. Nevertheless, we acknowledge that there could be more alternative omitted variables that could behave similar to organizational complexity but are fundamentally different. While acknowledging that such alternative omitted variables may offer different explanations of the association between organizational complexity and PEAD, we suggest that it is almost impossible to control for all such alternative scenarios. In conclusion, we do not claim to solve all omitted variables problems.

its interaction with *SUE* added.[31] 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 Panel A. First, the regression estimates suggest that PEAD is 1.45% (per three months after the announcement) for single-segment firms and 2.28% for established conglomerates (firms that have been conglomerates for more than two years) when we use the difference between the 95th and fifth percentiles of *SUE* (see Panel A1 of Table 1) to calculate differences in PEAD.[32] Treating new conglomerates as a separate group reduces the economic significance of the interaction term between *SUE* and the conglomerate dummy (which now represents only established conglomerates) by about a third (as compared with column four of Table 3) while not affecting its statistical significance. This suggests that stronger PEAD 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 established conglomerates. The product of *SUE* and *NewConglo* dummy is statistically significant, and its coefficient implies that, for an average new conglomerate, PEAD is 3.77% per three months, about 65% larger than that of an established conglomerate.

How are new conglomerates created? In roughly two-thirds of the cases, we can trace the increase in the number of segments to mergers and acquisitions using SDC data.[33] In the other third of the cases, it appears that the firm expands from within, starting a new line of business.

In the next two columns of Panel A, we try to estimate the PEAD 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 PEAD 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 mergers and acquisitions or via expansion from within leads to more confusion on the part of investors. On the one hand, firms may prefer to expand through mergers and acquisitions when venturing into more distant industries, as they lack the expertise to develop a business line from within. Expansion through mergers

31 Since the number of new conglomerates is low, in Panel A of Table 6 we do not control for # Analysts. Requiring that new conglomerates have non-missing analyst coverage data leaves us, in some years that have little M&A/conglomeration activity, with new conglomerates numbering in low double-digits and even in single digits.

32 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 2.5th percentiles of SUE.

33 SDC data includes both public and private firms. We include acquisitions of both public and private targets as potential ways of adding a new segment through mergers and acquisitions.

Table 6 Differences in PEAD among conglomerates

Panel A. PEAD and new conglomerates

	1	2	3
SUE	0.143	0.143	0.141
	(4.83)	*(4.76)*	*(4.79)*
SUE*Conglo	0.083	0.096	0.069
	(2.40)	*(2.62)*	*(2.05)*
SUE*NewConglo	0.148		
	(2.01)		
SUE*M&A		0.013	
		(0.10)	
SUE*NoM&A			0.635
			(1.96)
Conglo	-0.004	-0.004	-0.004
	(-2.56)	*(-2.67)*	*(-2.62)*
NewConglo	-0.003	-0.002	-0.003
	(-1.76)	*(-0.81)*	*(-1.18)*
Controls	YES	YES	YES
SUE*Controls	YES	YES	YES
# Observations	232,506	232,506	232,506

Panel B. PEAD in the conglomerates only sample

	1	2	3	4
SUE	0.033	0.115	-0.226	-0.011
	(1.63)	*(3.54)*	*(-2.12)*	*(-0.06)*
LogHTSD	-0.002	-0.001		
	(-1.22)	*(-0.77)*		
SUE*LogHTSD	0.122	0.106		
	(3.14)	*(2.45)*		
LogCOLV			-0.002	-0.001
			(-1.24)	*(-0.90)*
SUE*LogCOLV			0.197	0.201
			(4.05)	*(3.29)*
Controls	NO	YES	NO	YES
SUE*Controls	NO	YES	NO	YES
# Observations	40,239	40,239	38,976	38,976

Note: Panel A presents the results for quarterly Fama–MacBeth regressions of size- and market-to-book-adjusted cumulative returns in the 60 trading days following earnings announcements (CAR (2;60)) on earnings surprise (*SUE*), interactions of SUE with the conglomerate dummy complexity (*Conglo*), and with a dummy variable for newly created conglomerates (*NewConglo*). The regressions are performed every calendar quarter using the most recently computed SUE per firm. *NewConglo* dummy is equal to one for two years after a firm becomes a conglomerate 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 (cannot) be attributed to diversifying mergers and acquisitions. Panel B presents the results for similar Fama–MacBeth regressions on earnings surprise, SUE, and its interactions with *HTSD* and *COLV*. *HTSD* measures dispersion in segment growth rates. *COLV* is the standard deviation of a firm's sales weighted operating leverage divided by the equally weighted average operating leverage of its segments. *LogHTSD/LogCOLV* is the natural logarithm of one plus *HTSD/COLV*. Seg-

Table 6 (continued)

ments are counted as distinct business units if they can be assigned to different two-digit SIC industries. The regressions in the table also control for the interactions of SUE with market-to-book (*MB*), log of market cap (*Size*), institutional ownership (*IO*), a quarterly loss dummy (*Loss*), a measure of transaction costs (*Amihud*), and the variables themselves. One more control that is not interacted with *SUE* is momentum (*Mom*). Detailed definitions of all variables are in Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in italics. 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*

and acquisitions can also catch investors by surprise. When firms develop a new line of business, such internal growth usually takes time, whereas mergers and acquisitions are not necessarily predictable in advance. These considerations would suggest that stronger PEAD for new conglomerates could be more attributable to new conglomerates formed through mergers and acquisitions. On the other hand, both the acquirer and the target receive a lot of scrutiny during a merger, and the target has a history as a standalone firm before the merger. Such scrutiny and the availability of historical information about the target might suggest that higher PEAD for new conglomerates might be driven by new conglomerates formed via expansion from within rather than those that are formed through mergers and acquisitions.

Results strongly support the latter view. In column (2), which singles out new conglomerates created through mergers, we find that PEAD for these new conglomerates is indistinguishable from PEAD for existing conglomerates. (The difference, measured by the slope on the product of *SUE* and *NewCongloM&A*, is statistically and economically insignificant.) In column (3) though, we discover a dramatic difference in PEAD of new conglomerates that are created from within (i.e., not through a merger) and PEAD of existing conglomerates. Substituting the difference in *SUE* between the 95$^{\text{th}}$ and fifth percentiles into the regression in column (3), we estimate the average PEAD for single-segment firms at 1.42%, the average PEAD of existing conglomerates at 2.12%, and the average PEAD of new conglomerates created from within at a whopping 8.53% (per three months after the announcement). We conclude that 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.

Results in Panel A of Table 6 strongly suggest that the increase in organizational complexity (defined as the change in the conglomerate status) is associated with a significant increase in PEAD, consistent with our hypothesis that it is organizational complexity (and not any other characteristic driving the conglomerate status) that creates stronger PEAD. We also find that investors are most confused about firms that expand from within, that is, about those firms that add segments without being involved in mergers and acquisitions.

4.6 Does the degree of complexity matter?

In this subsection, we investigate whether PEAD is stronger for more complicated conglomerates by using two alternative measures of complexity. We follow

Hirshleifer and Teoh (2003) in constructing our first measure. 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 individual segments' earnings growth rates, conglomerates will be mispriced. Hirshleifer and Teoh (2003) suggest that the level of mispricing (cognitive processing costs) will increase with the dispersion of the segment growth rates.

We call our first empirical proxy of conglomerate complexity measure Hirshleifer-Teoh-Segment-Dispersion (HTSD) and calculate it as $\mathrm{HTSD} = \sum_{i=1}^{N} (e_i - f)^2 * s_i$, 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 the measure's high skewness.

Our second measure accounts for the realization that, even if an investor knows the exact sales figures generated by each segment, it would be difficult to predict the impact of the segment-level sales figures on the conglomerate's overall profits without understanding the unique cost structures of the distinct segments. Thus, we propose that differences in the cost structures of disparate business segments can introduce cognitive processing costs similar to those proposed by Hirshleifer and Teoh (2003). Inspired by Rajan et al. (2000), we estimate the divergence of a firm's cost structure with the coefficient of variation of operating leverage (COLV).[34] This measure is the standard deviation of a firm's sales weighted operating leverage divided by the equally weighted average operating leverage of its segments, where each i corresponds to a segment, s_i captures the sales share for segment i, and OL_i corresponds to the operating leverage of segment i, as follows.

$$\mathrm{COLV} = \frac{\sqrt{\sum_{i=1}^{n} \frac{\left(s_i * OL_i - \overline{\mathrm{s} * \mathrm{OL}}\right)^2}{n-1}}}{\sum_{i=1}^{n} \frac{OL_i}{n}}$$

In Panel B of Table 6, we focus on the conglomerate-only sample and investigate whether conglomerates with higher Hirshleifer-Teoh-Segment-Dispersion and higher coefficient of variation of operating leverage have higher PEAD. In the first column of Panel B, we regress CAR (2,60) on *SUE* and the interaction of log of (1 + *HTSD*) with *SUE* as well as on log of (1 + *HTSD*) itself. Column 2 additionally controls for size, market-to-book, momentum, loss, Amihud, and their interactions with *SUE*.[35] In both cases, we find that conglomerates with greater segment

[34] Rajan, Servaes, and Zingales (2000) measure the diversity of investment opportunities among the segments of a conglomerate as they study how this diversity affects internal capital allocations.

[35] Momentum is not interacted with SUE. As in Panel A, we have to exclude # Analysts from the set of controls, since requiring nonmissing # Analysts would have left us with too few observations for the required analyses.

earnings growth dispersion have larger post-earnings announcement drifts: the *SUE**log(1 + *HTSD*) term is positive and statistically significant. The interaction term in column two indicates that, assuming that all control variables are at their means, the PEAD returns based on the 95th and fifth (97.5th and 2.5th) SUE percentiles for a conglomerate that is in the top complexity decile would be 2.61% (5.10%) more than PEAD for a conglomerate that is in the bottom complexity decile based on the Hirshleifer-Teoh-Segment-Dispersion.[36]

In columns three and four, we similarly investigate the role that diversity of operating leverage plays in determining PEAD. Coefficient on the interaction of *SUE* with log(1 + *COLV*) is positive and highly statistically significant. Results in column (4) would suggest that, for an average conglomerate PEAD would increase by 1.71% for an increase of one standard deviation in log(1 + *COLV*), which equals 0.845. This finding implies that, while PEAD, based on the spread in *SUE* between the 95th and fifth percentile, is 4.1% for an average conglomerate with log(1 + *COLV*) = 2.08, PEAD goes up to full 6.93% for a similar conglomerate that is in the 90th percentile of the coefficient of variation of operating leverage. Overall, our results imply, as we predict, that it is cognitively taxing for investors to process earnings announcements of conglomerates with vastly different cost structures across segments. These results also help establish the fact that the degree of complexity also matters in determining the magnitude of PEAD.

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 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 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 of Cohen and Lou

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36 The average for log(1 + HTSD) is 0.783 among conglomerates. The 90th percentile value of log(1 + HTSD) is 2.448, while the 10th percentile value for log(1 + HTSD) is 0.0046.

(2012) lasts for only one month, whereas the stronger PEAD for conglomerates lasts throughout the quarter.[37]

In Table 7, we explicitly control for pseudo-conglomerate returns (*PCRet*) by adding it along with its interaction with SUE to the lengthy list of control variables in our main regression of CARs on *SUE*. Following Cohen and Lou (2012), *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 must include both single-segment firms and conglomerates to compare the PEAD for the two types of firms, we have to substitute an alternative variable for *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.[38]

In the first column of Table 7, we regress CARs on *SUE*, *PCRET* itself, and 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 interaction with the conglomerate dummy is statistically significant. In the second column of Table 7, we add the interaction of *SUE* with *Conglo* to the list of controls and find that the interaction between *PCRet* and *Conglo* is no longer significant.

The other two columns of Table 7 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 estimated after controlling for the predictability documented by Cohen and Lou (2012) are similar in magnitude to the slopes estimated earlier in Table 3, and the slope on the interaction between *PCRET* and *Conglo* is now marginally significant. We conclude that the stronger PEAD experienced by conglomerates is a separate phenomenon that has little overlap with the Cohen and Lou (2012) predictability of conglomerate returns using returns to pseudo-conglomerates.

5.2 Controlling for alternative explanations of PEAD

In Table 8, we control for the potential impact of many alternative explanations of the post-earnings announcement drift anomaly. 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 et al. 2010;

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

[38] 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 a slight 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.

Lehavy et al. 2011; Lee 2012), analyst responsiveness (Zhang 2008), earnings volatility (Cao and Narayanamoorthy 2012), and the impact of the quality of earnings information (Francis et al. 2007) on PEAD in an effort to distinguish the impact of organizational complexity on PEAD.

The first column in Table 8 estimates the relation between PEAD and conglomerate status controlling for the effect of market-to-book, size, institutional ownership, loss, Amihud, the interactions of this extensive list of control variables with *SUE*, and the momentum (Mom) control. We use the results in column (1) of Table 8 as a benchmark for the other columns in Table 8.[39]

In the second column of Table 8, 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).[40] 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 interaction 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* does not reduce the loading on the interaction term between *SUE* and the conglomerate dummy.

The fourth and fifth columns investigate the impact of organizational 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).[41] In column (4), we investigate the impact of organizational complexity on PEAD for the subset of firms for which we have textual complexity information. Column (4) reveals results consistent with our basic findings, as conglomerates have higher PEAD compared to single-segment firms with similar characteristics in this subsample 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 significant, suggesting that the post-earnings announcement drift anomaly in fact seems to be smaller for firms with higher disclosure complexity. We believe this result could 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.[42] Controlling for *FOG* does not affect our results, as the interaction of *SUE* with *Conglo* in column (5) is virtually indistinguishable from the results in column (4).

In columns (6) and (7), we construct a measure of analyst responsiveness (DRESP), following Zhang (2008), and investigate whether controlling for its interaction with *SUE* could reduce the impact of organizational complexity on PEAD. Column (6) reveals that our basic results go through for the subsample of firms with

[39] In Table 8, we do not control for *# Analysts*, as requiring nonmissing variables of analyst coverage would significantly reduce the sample in some years in several columns of Table 8.

[40] 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).

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

[42] Future research may attempt to decompose FOG into innate business-complexity and managerial obfuscation components, following Bushee et al. (2017), and analyze the impact of these components on PEAD separately.

Table 7 Robustness: Controlling for potential spillover from industry-wide information events on PEAD

Complexity measure	Conglo 1	Conglo 2	Comp 3	Nseg 4
SUE	0.150	0.113	0.110	0.052
	(3.81)	*(2.87)*	*(2.68)*	*(0.96)*
SUE*Complexity		0.132	0.350	0.068
		(2.37)	*(2.58)*	*(2.11)*
PCRet* Complexity	0.047	0.029	0.070	0.018
	(2.35)	*(1.31)*	*(1.42)*	*(1.33)*
Complexity		-0.001	-0.002	0.000
		(-0.38)	*(-0.43)*	*(-0.37)*
PCRet	-0.010	-0.005	-0.005	-0.024
	(-0.47)	*(-0.24)*	*(-0.23)*	*(-0.90)*
Controls	YES	YES	YES	YES
SUE*Controls	YES	YES	YES	YES
# Observations	112,443	112,443	112,443	112,443

Note: This table presents the results for quarterly Fama–MacBeth regressions of size- and market-to-book-adjusted cumulative returns in the 60 trading days following earnings announcements (CAR(2;60)) on earnings surprise (*SUE*), interaction of *SUE* with *Conglo*, interactions of (*SUE)* with the recurring control variables, as well as *Conglo* and the usual control variables themselves. We also control for the impact of industry-wide information events, estimated via pseudo-conglomerate returns (*PCRet*), in all columns. The regressions are performed every calendar quarter using the most recently computed SUE per firm. Recurring control variables include market-to-book (*MB*), size (*Size*), institutional ownership (*IO*), loss dummy (*Loss*), transaction costs (*Amihud*), and the number of analysts (*# Analysts*). One more control that is not interacted with *SUE* is momentum (*Mom*). Innate business complexity, *Comp*, is 1-HHI, where HHI is the Herfindahl index computed using segment sales shares within a conglomerate. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in italics. 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*

available *DRESP* information. In column (7), we find that the interaction of *SUE* with *DRESP* is negative, qualitatively in line with Zhang's (2008) prediction that more responsive analysts help investors react to earnings in a timelier manner.[43] Controlling for the impact of analyst responsiveness does not change our basic result regarding the impact of organizational complexity on PEAD.

In a recent paper, Cao and Narayanamoorthy (2012) show that firms with lower earnings volatility (trading frictions) have higher earnings surprise (SUE) persistence, leading to higher 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 earnings volatility, calculated

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

Table 8 Robustness: Controlling for alternative explanations of PEAD

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
SUE	0.134	0.146	0.141	0.127	0.137	-0.038	0.057	0.148	0.156	0.127	0.144	0.134	0.126	-0.051	0.204
	(4.70)	*(4.69)*	*(4.52)*	*(2.83)*	*(3.03)*	*(-0.60)*	*(0.48)*	*(4.84)*	*(4.37)*	*(2.24)*	*(2.56)*	*(4.72)*	*(4.60)*	*(-0.37)*	*(0.70)*
SUE*Conglo	0.090	0.056	0.065	0.083	0.076	0.252	0.257	0.084	0.073	0.120	0.123	0.090	0.089	0.337	0.305
	(2.59)	*(1.55)*	*(1.86)*	*(1.92)*	*(1.84)*	*(2.74)*	*(2.77)*	*(2.37)*	*(2.02)*	*(1.66)*	*(1.73)*	*(2.60)*	*(2.52)*	*(2.63)*	*(2.75)*
SUE*EP			0.011												-0.031
			(0.90)												*(-0.71)*
SUE*FOG					-0.033										0.050
					(-1.48)										*(1.10)*
SUE*DRESP							-0.362								-0.349
							(-1.31)								*(-1.52)*
SUE*EarnVol									-0.008						0.015
									(-0.62)						*(0.26)*
SUE*VolDA											0.056				0.117
											(1.33)				*(1.21)*
SUE*IVol													0.047		-0.005
													(1.89)		*(-0.06)*
Conglo	-0.004	-0.004	-0.004	-0.004	-0.004	0.002	0.002	-0.004	-0.004	-0.003	-0.003	-0.004	-0.005	-0.006	-0.007
	(-2.30)	*(-2.36)*	*(-2.33)*	*(-1.65)*	*(-1.67)*	*(0.69)*	*(0.86)*	*(-2.51)*	*(-2.42)*	*(-1.74)*	*(-1.73)*	*(-2.29)*	*(-2.77)*	*(-2.40)*	*(-2.51)*
EP			0.000												0.000
			(-0.29)												*(0.04)*
FOG					0.001										0.002
					(0.94)										*(0.92)*
DRESP							0.008								0.011
							(1.98)								*(2.26)*
EarnVol									-0.001						-0.001

Table 8 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
									(-1.78)						*(-0.38)*
VolDA											0.001				0.001
											(0.75)				*(1.44)*
IVol													-0.009		-0.009
													(-3.96)		*(-2.56)*
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
SUE*Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
# Observations	233,065	173,338	173,338	114,684	114,684	87,318	87,318	218,541	218,541	67,325	67,325	233,033	233,033	24,651	24,651

Note: This table presents the results for quarterly Fama–MacBeth regressions of size- and market-to-book-adjusted cumulative returns in the 60 trading days 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*), and a measure of transaction costs (*Amihud*). One more control that is not interacted with *SUE* is momentum (*Mom*). Where appropriate, we also control for time-varying earnings persistence (*EP*), textual complexity (*FOG*), analyst responsiveness (*DRESP*), earnings volatility (*EarnVol*), earnings quality (*VolDA*), and idiosyncratic volatility (IVol). The regressions are performed every calendar quarter using the most recently computed SUE per firm. Even-numbered columns restrict the sample to only firms for which the new control variable from the following column is available (e.g., column two requires EP to be available, but EP is only controlled for in column three). 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 following 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)* that equals 1 if at least one analyst following firm j in quarter t is responsive to earnings announcements and 0 otherwise. Earnings volatility (*EarnVol*) is calculated following Cao and Narayanamoorthy (2012). (*VolDA*) captures the information quality of earnings and is defined as the coefficient of variation (standard deviation divided by average) of discretionary accruals computed following Dechow and Dichev (2002). IVol is standard deviation of residuals from the three-factor Fama and French (1993) model, with the three-factor model fitted to daily returns separately in each firm-quarter. Detailed definitions of all control 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 italics. 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 9 Robustness: Joint impact of organizational complexity and investor sophistication on PEAD

Institutional ownership quintiles	Low	Quintile 2	Quintile 3	Quintile 4	High
SUE	0.359	0.339	0.268	0.152	0.222
	(3.00)	*(2.53)*	*(2.80)*	*(1.87)*	*(1.74)*
SUE*Conglo	0.246	0.317	0.222	0.152	-0.050
	(2.05)	*(1.91)*	*(1.54)*	*(1.15)*	*(-0.22)*
Conglo	-0.002	-0.009	0.001	0.002	0.004
	(-0.49)	*(-2.64)*	*(0.39)*	*(0.88)*	*(1.61)*
Controls	YES	YES	YES	YES	YES
SUE*Controls	YES	YES	YES	YES	YES
# 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 market-to-book-adjusted cumulative returns in the 60 trading days (one-quarter) following earnings announcements (CAR(2;60)) on earnings surprise, SUE, and its interaction with organizational complexity, measured using the *Conglo* dummy, in five distinct cross-sections sorted based on the percentage owned by institutions *(IO)*. The regressions are performed every calendar quarter using the most recently computed SUE per firm. *Conglo* is equal to one if the firm is a conglomerate and zero otherwise. 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), institutional ownership is in the second lowest quintile. In column (3), we limit our analyses to firm-quarters where (*IO*) is in the median quintile. In column (4), we use firm-quarters in the second highest (*IO*) 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 (*Size*), quarterly loss dummy (*Loss*), transaction costs (*Amihud*), and the number of analysts (*# Analysts*) as well as (*Conglo*), (*MB*), (*Size*), (*Loss*), (*Amihud*), and (*# Analysts*) themselves. One more control that is not interacted with *SUE* is momentum (*Mom*). The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in italics 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

following Cao and Narayanamoorthy (2012). We find that our results are virtually the same as the full-sample results. In column (9), we explicitly control for the impact of earnings volatility on PEAD. Our results are consistent with those of Cao and Narayanamoorthy (2012)—higher earnings volatility leads to lower PEAD, as evidenced by the negative coefficient on the interaction of *SUE* and *EarnVo*l. This, however, barely affects our main finding as the interaction of *SUE* with *Conglo* is slightly reduced from 0.084 to 0.073 and remains statistically significant. The lack of overlap between *Conglo* and earnings volatility is consistent with the evidence in Panel B3 of Table 1 that conglomerate status, unlike earnings volatility, is unrelated to earnings persistence.

In a related paper, Francis et al. (2007) document that PEAD is larger for firms that have poorer earnings quality. In particular, Francis et al. (2007) measure earnings quality as the coefficient of variation, standard deviation divided by average, of discretionary accruals (VolDA), computed following Dechow and Dichev (2002). In column (10), we analyze the impact of organizational structure on PEAD for a subset of firms, for which we can measure earnings quality. We find that our results

Table 10 Robustness: Accounting for nonlinearity in SUE and using alternative CAR measures in PEAD regressions

	Carhart alphas			Winsorized SUE			SUE as decile rank		
Complexity measure	1 (Conglo)	2 (Comp)	3 (NSeg)	4 (Conglo)	5 (Comp)	6 (NSeg)	7 (Conglo)	8 (Comp)	9 (NSeg)
SUE	0.060	0.057	0.016	0.417	0.429	0.276	0.021	0.022	0.014
	(1.29)	*(1.23)*	*(0.26)*	*(5.08)*	*(5.10)*	*(2.40)*	*(4.18)*	*(5.10)*	*(2.11)*
SUE* Complexity	0.123	0.325	0.054	0.227	0.548	0.143	0.010	0.014	0.006
	(2.11)	*(2.31)*	*(1.74)*	*(1.97)*	*(1.82)*	*(2.19)*	*(1.87)*	*(1.64)*	*(2.35)*
Complexity	-0.005	-0.009	-0.003	-0.001	-0.002	0.000	-0.002	-0.001	-0.001
	(-2.44)	*(-2.03)*	*(-2.87)*	*(-0.34)*	*(-0.39)*	*(-0.39)*	*(-1.27)*	*(-0.23)*	*(-1.41)*
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
SUE*Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
# Observations	113,092	113,092	113,092	113,388	113,388	113,388	113,388	113,388	113,388

Note: This table presents the results for quarterly Fama–MacBeth regressions of firm-specific Carhart alphas in the 60 trading days following earnings announcements $\alpha_C(2;60)$) on earnings surprise (*SUE*), interactions of *SUE* with three different measures of organizational complexity (*Conglo*, *Comp*, and *Nseg*), interactions of SUE with a recurring set of standard controls (*Size*, *MB*, *IO*, *Loss*, *Amihud*, and *# Analysts*) as well as the controls themselves. One more control that is not interacted with *SUE* is momentum (*Mom*). The regressions are performed every calendar quarter using the most recently computed SUE per firm. 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. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation and are reported below each coefficient in italics 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* are qualitatively the same as the full-sample results. In column (11), we explicitly control for the impact of earnings quality on PEAD and find that our basic findings do not change, as the coefficient on the interaction of *Conglo* with *SUE* is almost the same as the one in column (10).

Mendenhall (2004) finds that high *IVol* (idiosyncratic volatility) firms have stronger PEAD, consistent with arbitrage risk being an obstacle in exploiting the mispricing. In column (12), we re-run our main regression in the sample with non-missing *IVol* and find no visible changes, as the number of firms with missing *IVol* among the firms with all control variables nonmissing is exceedingly small. In column (13), we use both the *SUE-IVol* and *SUE-Conglo* interaction in one regression: we confirm the result of Mendenhall (2004) and find that the slope on the *SUE-IVol* interaction is positive and marginally significant, but the presence of the *SUE-IVol* interaction has virtually no effect on the slope on the *SUE-Conglo* product.

Finally, in columns (14) and (15), we study the impact of organizational complexity on PEAD in a sample where we simultaneously control for the impact of *MB*, *size*, *IO*, *loss*, *Amihud*, *Conglo*, *EP*, *FOG*, *DRESP*, *EarnVol*, *IVol*, and *VolDA* along with their interactions with SUE and find, in column (15), that the interaction of *SUE* with *Conglo* is statistically and economically significant, even in this kitchen sink regression, verifying the distinctiveness of the effect we have uncovered.

5.3 Controlling for the joint impact of investor sophistication and firm complexity on PEAD

Since the work of 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. attribute this to unsophisticated investors' mistaken assumption that the process that underlies earnings is a seasonal random walk. Bartov et al. suggest and document that sophisticated investors understand the pricing implications of earnings surprises better, and, for this reason, there is less mispricing and lower PEAD in stocks largely held by institutional investors. We control for the interaction of institutional ownership (IO) with organizational 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 9, we take a step further and analyze the joint impact of organizational 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 from Panel A of Table 3 separately in each quintile. Our results indicate that, in *IO* quintiles 1 and 2, PEAD is economically and statistically larger for conglomerates than for single segment firms. In *IO* quintiles 3 and 4, PEAD for conglomerates is economically larger but statistically not significantly different from PEAD for single segment firms. In *IO* quintile 5, where investor sophistication is at its highest, PEAD for conglomerates is about the same as the PEAD for single segment firms. While using the smaller subsamples 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 subsample of firms with the largest institutional ownership, sophisticated investors fully eliminate the adverse effects of organizational complexity on mispricing.

5.4 Using alternative CAR measures and accounting for nonlinearity in SUE

In our final set of robustness checks, 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 as the dependent variable. In particular, we run quarterly Fama–MacBeth regressions of firm-specific Carhart alphas cumulated in the 60 trading days (one-quarter) following earnings announcements (αC(2;60)) on earnings surprise (SUE), interactions of *SUE* with measures of organizational complexity (*Conglo*, *Comp*, and *NSeg*) and the standard controls (*MB, size, IO, loss, Amihud*, and *# Analysts*) as well as their interactions with *SUE* and the momentum (Mom) control.

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 to account for the nonlinear 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 nonlinearity mentioned earlier as well as 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 remarkably similar results to those observed in Table 3, suggesting that whether we use size-and-BM adjusted returns or Carhart alphas, we find larger PEAD for organizationally more complicated firms.

Similarly, winsorizing *SUE* values at the fifth and 95th percentiles every quarter does not change our results. In columns (4) through (6), we find that the interaction of *SUE* with measures of organizational complexity are all positive and economically as well as statistically significant, indicating higher PEAD for conglomerates. 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 more complicated firms. In all specifications, we find that conglomerates have PEAD 25% to 50% larger than the PEAD for single-segment firms. Results in columns (7) through (9) add further evidence to the tradability of this strategy, as it utilizes decile portfolios.[44]

[44] Results in column (7) suggest that, for an average single-segment firm, the hedge return to buying the highest SUE decile and selling the lowest SUE decile is 2.72%, while for a similar conglomerate the hedge return for the same trading strategy would be 3.95%. The difference is 1.23% for the three months after the earnings announcement and is tradable.

6 Conclusion

We document that information about complex firms is harder to process, and we predict therefore that PEAD is stronger for complex firms. Using organizational structure as our proxy for organizational complexity, we find that more complicated firms—conglomerates—have PEAD that is twice as large, compared to simpler firms (single-segment firms) with the same level of unexpected earnings surprise (SUE).

We attribute our findings to the fact that it is more costly and difficult to process firm-specific earnings information about complicated firms. We show that, once we control for firm size and other relevant firm characteristics, conglomerates have lower institutional ownership and smaller presence of short sellers than single-segment firms do. This lack of sophisticated investors leads to less efficient pricing and stronger PEAD for conglomerates. We also find that, for a similar reason, conglomerates are covered by fewer analysts and those analysts make larger forecast errors, compared to single-segment firms with similar firm characteristics. We conclude that relatively less information is produced about conglomerates, which leads to less efficient pricing and stronger PEAD for conglomerates.

We also find that the earnings announcement reaction is 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, as evidenced by larger delayed response ratios for conglomerates (60.5%), compared to single-segment firms (44.6%).

To address the concern that conglomerate status relates to an unknown variable that also affects the strength of PEAD, we re-examine the effect of complexity on PEAD focusing on periods right after a conglomerate is formed. Consistent with our slower-information-processing hypothesis, PEAD is stronger for new conglomerates than for existing ones. We also find that investors are most confused about firms that expand from within rather than firms that diversify into a new industry via mergers and acquisitions (and receive significant public scrutiny in the process).

Hirshleifer and Teoh's (2003) model predicts that more complicated conglomerates, that is, those with greater dispersion in the growth rates of their segment-level earnings, face larger mispricing. We show empirically that such complicated conglomerates have stronger PEAD. We also use an alternative measure of a conglomerate's complexity based on the divergence in the cost structures of a conglomerate's segments and find that conglomerates have stronger PEAD if operating leverage of their segments is vastly different. Our analysis indicates that, as segments of a conglomerate become more dissimilar, the cognitive costs of processing information in their earnings increase, which leads to larger PEAD for more complicated conglomerates.

Our results are robust to controlling for the impact of analyst responsiveness, earnings volatility, time-varying earnings persistence, earnings quality, and disclosure complexity on PEAD. We also show that the relation between PEAD and organizational complexity is stronger among firms with lower institutional ownership. This finding suggests that sophisticated investors' preference not to invest in organizationally complicated firms significantly impacts the level of mispricing uncovered in this paper. Finally, we show that our results go through when we use Carhart alphas, three-factor Fama–French alphas, six-factor Fama–French alphas, or Daniel et al. (1997) alphas, instead of size-BM adjusted returns, and that our conclusions are robust to alternative definitions of *SUE*, such as using *SUE* values winsorized at 0.5% (99.5%/0.5%), 5% (95%/5%), using *SUE* values based on analyst forecasts, standardizing *SUE* values by its cross-sectional standard deviation, or simply using SUE deciles.

We conclude that organizational complexity, proxied via organizational structure, has a profound effect on how investors process earnings-related information. Our analyses show that investors face large cognitive processing costs when analyzing conglomerates, which leads to stronger PEAD for conglomerates, especially for new conglomerates and conglomerates with diverse business segments.

Appendix

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

Age: Age measures firm age, following 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.

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

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): One if the firm is a conglomerate, zero 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.

HTSD (dispersion in segment growth rates): sum of squared deviations of segment-level earnings growth rates (based on item *ops* from Compustat Segments file) from the firm-level earnings growth rate. The squared deviations are weighed by squared share of the segment sales (item *sales* from Compustat Segments file) in total firm-level sales.

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-quarter (at least 40 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 one if the company incurred an operating loss in the immediate quarter, zero 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): one 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 standalone 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 to calculate a corresponding pseudo conglomerate return.

RDSales (research and development expenses to sales): Rdsales is the ratio of R&D expense to sales.

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.

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

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

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 or 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.

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.

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