Complicated Firms*

Lauren Cohen
Harvard Business School and NBER

Dong Lou
London School of Economics

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ABSTRACT

We exploit a novel setting in which the same piece of information affects two sets of firms: one set of firms requires straightforward processing to update prices, while the other set requires more complicated analyses to incorporate the same piece of information into prices. We document substantial return predictability from the set of easy-to-analyze firms to their more complicated peers. Specifically, a simple portfolio strategy that takes advantage of this straightforward vs. complicated information processing classification yields returns of 118 basis points per month. Consistent with processing complexity driving the return relation, we further show that the more complicated the firm, the more pronounced the return predictability. In addition, we find that sell-side analysts are subject to these same information processing constraints, as their forecast revisions of easy-to-analyze firms predict their future revisions of more complicated firms.

JEL Classification: G10, G11, G14.

Key words: Complicated processing, return predictability, standalone, conglomerate, market frictions.

1. Introduction

In some form, most asset pricing models have agents collect, interpret, and trade on information, continuing until prices are updated to fully reflect available information. Understanding which frictions prevent these information revelation mechanisms from working properly not only furthers our empirical grasp of information flows in financial markets, but also provides a more solid base for theoretical frameworks of information diffusion. In this paper, we quantify how frictions in the processing of information impact the way information is incorporated into firm values. To do this, we use a novel approach of taking two sets of firms that are both subject to the same information shocks. The only difference is that one set of firms requires more complicated information processing to impound the same piece of information into prices than the other. Using this straightforward vs. complicated information processing classification, we show that frictions and constraints that impede information processing can result in substantive predictability in the cross section of asset prices.

To be more specific, we examine information events that affect an entire industry. We then exploit the fact that, while it is relatively straightforward to incorporate industry-specific information into a firm operating solely in that industry (i.e., a standalone firm), it generally requires a set of more complicated analyses to impound the same piece of information into the price of a firm with multiple operating segments (i.e., a conglomerate firm). For instance, imagine new research suggests that chocolate increases life expectancy. To incorporate this information into the price of a focused chocolate producer, Chocolate Co., would be a straightforward and unambiguous task, as the firm only receives revenues from making chocolate. In contrast, to incorporate this positive chocolate industry shock into the price of a conglomerate firm that makes chocolate, tacos, and light bulbs (call it CTB Inc.) would be more difficult, as the percentage of aggregate revenues contributed by each industry segment varies over time, and thus requires an increased amount of research and processing capacity.

This paper simply posits that given investors' limited processing and capital capacity, complexity in information processing can lead to a significant delay in the impounding of information into asset prices. More specifically, we predict that the positive information about the chocolate industry be reflected in the prices of these easy-to-analyze firms (e.g., Chocolate Co.) first, which will therefore predict the future updating of the same piece of information into the prices of their more complicated peers (e.g., CTB, Inc.).

To test for the return effect induced by complications in information processing, we implement the following simple portfolio strategy. For each conglomerate firm we construct a "pseudo-conglomerate" (PC) that consists of a portfolio of the conglomerate firm's segments made up using only standalone firms from the respective industries. So, for the example of the conglomerate firm above (CTB, Inc. - chocolate, tacos, light bulbs), assume that chocolate makes up 40% of its sales, tacos make up another 30%, and light bulbs make up the remaining 30%. CTB's corresponding "pseudo-conglomerate" would then be: 0.4*(a portfolio of all chocolate standalones) + 0.3*(a portfolio of all taco standalones) + 0.3*(a portfolio of all light bulb standalones).

We can easily calculate the performance of each pseudo-conglomerate by aggregating the value-weighted average returns of the standalone firms within each of the conglomerate firm's industries. As these pseudo-conglomerates are composed of (relatively) easy-to-analyze firms subject to the same industry shocks, their prices should be updated, and thus reflect the information, first. Consequently, the returns of these pseudo-conglomerate portfolios should *predict* the future updating to the same information shocks - i.e., future returns - of their paired conglomerate firms.

We then sort conglomerate firms into decile portfolios based on lagged returns of their corresponding pseudo-conglomerates, and find strong evidence that complexity in information processing can cause significant return predictability in the cross-section of stocks. Specifically, a portfolio that goes long in those conglomerate firms whose corresponding pseudo-conglomerates performed best in the prior month and goes short in those conglomerate firms whose pseudo-conglomerates performed worst in the prior month, has value-weighted returns of 95 basis points (t=3.18) in the following month. For the analogous equal-weighted portfolio, the returns are 118 basis points per month (t=5.51). Both results are virtually unaffected when controls for size, book-to-market, past returns, and liquidity are included. Further, we observe no sign of any return reversal in the future. This robust return pattern helps confirm that we truly are capturing a mechanism of delayed updating of conglomerate firm prices to information important to their fundamental values.

Note a few important things about these complicated-processing portfolios that distinguish our findings from prior research. This is not a traditional momentum effect in the sense that the return of the same stock or portfolio (e.g., industry) predicts itself, as our strategy relies on the returns of one set of firms being able to predict the price movements of an entirely different set of firms. More specifically, our findings are not driven by the industry momentum effect identified by Moskowitz and Grinblatt (1999), as our results remain highly significant even after applying various controls for past value-weighted industry returns.[1] Nor are our findings consistent with a pure investor inattention story. We show that industry-specific shocks are updated into the prices of smaller firms (e.g., focused firms) first, and only then into the prices of larger conglomerate firms. In fact, this is the only anomaly in which, to our knowledge, predictability flows from smaller to larger firms, and so is unique in this sense. Lastly, our calendar-timer portfolio strategy trades only in conglomerate firms (larger firms on average), so liquidity and other microstructure issues have nearly no impact on our portfolio results.

To explore the mechanism in more depth, if our findings are truly driven by complications in information processing impeding material information from being impounded into conglomerate firm values, we would expect that the more complicated analyses that are required, the more severe the delay in incorporating information. We find strong support for this prediction in the data. Specifically, we show that the more diversified a firm's operations are across industries (measured by a Herfindahl index), thus requiring more complicated analyses to incorporate information about any single industry segment into conglomerate prices, the more pronounced the return predictability.

[1] The horizon of our return effect is also different from the industry momentum effect. While the return effect we document is large in the first month after portfolio formation and does not reverse subsequently, industry momentum continues for a year and reverses significantly starting in year two.

In a cleaner way, we perform a test looking at the *exact* same firms that switch status. Specifically, we look at standalones that transition to conglomerate firms. Although we have significantly fewer firms in the test, the advantage of this test is that we can examine information updating of the exact *same* firm when it requires easy vs. complicated information processing. The prediction is that when the same firm is a conglomerate, its corresponding pseudo-conglomerate's returns should be a stronger predictor of its future price movements than when it is a standalone. Consistent with this prediction, we find that the exact same firms have significantly predictable abnormal returns from their paired pseudo-conglomerates when they are conglomerate firms, but not when they are focused firms.

Our documented return patterns thus far are generally consistent with two interpretations: i) a complicated information processing channel, and ii) a complicated trading mechanism, where even if investors knew the exact weights of individual segments, and how a given piece of information would affect the complicated firm's value, it might still be difficult for them to undertake the complex set of trades needed to impound this information into the price. For instance, in the case of CTB Inc., if good information comes out about the chocolate industry, in the absence of information about tacos and light bulbs, and given that investors do not want to bear the information risk of these other segments, they would have to long the conglomerate (CTB Inc.), and then put on a series of trades to hedge out the risk of the other two segments. To distinguish between the two hypotheses, we examine the behavior of sell-side analysts on these same two sets of firms; while analysts may be subject to the same information processing constraints, they are not subject to any complicated trading frictions. We find evidence that analyst forecast revisions of focused firms significantly predict future forecast revisions of complicated firms, consistent with complicated information processing being the driving factor behind our documented patterns.

In a related vein, we examine the impact of this same complication on the transmission of non-fundamental shocks. Specifically, building upon prior evidence on categorical thinking, we test whether the complication in information processing is also a friction to categorization (i.e., complicated firms are more difficult to categorize than simple firms). Given that sentiment has been shown to often act at the level of categories, if complicated firms are more difficult to categorize, this would predict that sentiment-related return shocks should affect simple-to-analyze firms and complicated-to-analyze firms in different ways. We find evidence consistent with this prediction. In particular, we document that difficult to categorize firms are not subject to the shift away from fundamental value due to industry-wide sentiment, nor do they experience the subsequent reversal back to fundamental value. This is consistent with frictions to categorization (i.e., being a conglomerate firm) preventing complicated firms from being categorized, and thus from being subject to the same sentiment shocks as easy to categorize firms.

Finally, we run a number of additional tests to ensure the robustness of these results. We split our portfolios and find that this return predictability is robust across large and small firms, as well as high and low idiosyncratic risk stocks, and is also strong and significant using DGTW characteristics-adjusted stock returns. We also run all tests in the Fama-MacBeth framework to include a number of additional determinants of future returns (e.g., industry momentum, own-firm momentum, turnover, etc.). These controls have nearly no effect on the return predictability patterns we document. In addition, we obtain historical transaction cost data from a large asset management firm to calculate net returns to our portfolio strategy. While our net-return results taking into account these transaction costs are obviously lower, they remain economically meaningful and statistically significant.

The paper proceeds as follows. Section I lays out the background for the setting we examine in the paper. Section II presents our data collection procedures, and summary statistics. Section III provides our main results on the return predictability pattern caused by investors' complications in information processing. Section IV examines the mechanism in more detail, while Section V explores the impact of complications on exposure to sentiment shocks. Section VI conducts robustness checks and examines the horizon of the return effect. Section VII concludes.

2. Background

This paper is broadly related to prior studies that analyze investors' delayed and biased reactions to information. The basic theme of this strand of literature is that, if investors have limited resources and capacity to collect, interpret, and finally trade on value-relevant information, we would expect asset prices to incorporate information only gradually.

There is an extensive literature on investors' limited attention to information. On the theoretical front, a number of studies (e.g., Merton (1987), Hong and Stein (1999), and Hirshleifer and Teoh (2003)) argue that, in economies populated by investors with limited attention, delayed information revelation can generate expected returns that cannot be fully explained by traditional asset pricing models. Subsequent empirical studies find evidence that is largely consistent with these models' predictions. For example, Huberman and Regev (2001), Barber and Odean (2006), DellaVigna and Pollet (2006), Hou (2006), Menzly and Ozbas (2006), Hong, Torous, and Valkanov (2007), and Cohen and Frazzini (2008) find that investors respond quickly to information that attracts their attention (e.g., news printed on the New York Times, stocks that have had extreme returns or trading volume in the recent past, and stocks that more people follow), but tend to ignore information that is less salient yet material to firm values. In addition, investors' limited attention can result in significant asset return predictability in financial markets.

Prior research has also examined investors' biased interpretations of information. Kahneman and Tversky (1974) and Daniel, Hirshleifer, and Subrahmanyam (1998), among many others, argue that investors tend to attach too high a precision to their prior beliefs (or some initial values) and private signals, and too low a precision to public signals, which can result in predictable asset returns in subsequent periods. A large number of recent empirical studies confirm these predictions. For instance, Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), Hong, Lim and Stein (2000), Chan, Lakonishok and Sougiannis (2001), Ikenberry and Ramnath (2002), Hirschey and Richardson (2003), Kadiyala and Rau (2004), Zhang (2006) find that investors usually underreact to firm-specific (public) information (e.g., earnings reports, R&D

expenditures, goodwill write-offs, and etc.) and to various (publicly announced) corporate events (e.g., stock splits, share issuances and repurchases, and etc.); furthermore, investors' under- (over-) reaction leads to significant return predictability based only on publicly available information.

Duffie (2010) formalizes a number of these ideas in a model with frictions in how capital responds to trading opportunities. His framework fits well with both our frictions in information processing, and the strong empirical evidence we find for the impact of such frictions on asset price evolution.

Finally, this paper is also related to the extensive literature on the diversification discounts of conglomerate firms. While prior literature focuses primarily on the average valuation differences (i.e., "discounts") between diversified and their corresponding focused firms, our results, in contrast, are purely cross-sectional among diversified firms. Specifically, we explore how these diversified firms respond to important industry information shocks that were first updated into the prices of standalone firms. In particular, Lamont and Polk (2001) find that conglomerate firms with larger discounts have higher expected returns than those with lower discounts. However, as we show in Section III, this M/B-implied discount has no impact on the strong return predictability patterns we show in this paper.

3. Data

The main dataset used in this study is the financial data for each industry segment within a firm. Starting in 1976, all firms are required by SFAS No. 14 (Financial reporting for segments of a business enterprise, 1976) and No. 131 (Reporting desegregated information about a business enterprise, 1998) to report relevant financial information of any industry segment that comprises more than 10% of a firm's total consolidated yearly sales.[2] In particular, firms are required to report, among others,

[2] SFAS No. 131 which superseded No. 14 in 1998, differs from its predecessor in the way segments are defined. Under SFAS No. 131, firms are required to report segments consistent with the way in which management organizes the business internally; and in addition, the accounting items disclosed for each segment are defined consistent with internal segment information used to assess segment performance. This represents a significant change from SFAS No. 14, under which firms were required to disclose

assets, sales, earnings, and cash flows from operations in each industry segment. We extract firms' segment accounting and financial information from Compustat segment files. Given that the segment reporting practice was first enforced in 1976, our sample covers the period of 1977 to 2009.

Industries are defined based on two-digit SIC codes. For robustness checks, we also use alternative definitions of industries based on one-digit SIC codes and the Fama-French 48-industry classification. Since the results are qualitatively the same, those based on alternative industry definitions are untabulated. Standalone firms are defined as those operating in only one industry, and that the *segment* sales reported in Compustat segment files account for more than 80% of the *total* sales reported by the firm in Compustat annual files. This is to exclude, from our sample, firms that actually operate in multiple industries but fail to report financial data for some industry segments. Conglomerate firms are defined in a similar fashion; these are the firms operating in more than one industry and that the aggregate sales from all reported segments account for more than 80% of the total sales of the firm. The latter condition is to ensure that the sum of all segments of a conglomerate firm in our sample is fairly representative of the entirety of the firm.[3]

The Compustat sample is then merged with the CRSP monthly stock files. We require firms to have non-missing market equity and book equity data at the end of the previous fiscal-year end. To ensure that the segment information is publicly known before we conduct our stock return test, we impose at least a six-month gap between firm fiscal year ends and stock returns; specifically, we use segment financial information from a fiscal year only after June of the following year. Moreover, to reduce the impact of micro-cap stocks on our test results, we further exclude from our sample those stocks that are priced below five dollars a share at the beginning of the holding period. In

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segment information by both line-of-business and geographic area with no specific link to the internal organization of the firm.

[3] This is a simple data requirement, as there are many firms in the sample that have a number of segments below the 10% threshold, and so do not report separate segment data for them. We have experimented with different cutoffs (e.g., 70%, 75%, 85%, and 90%), and the results are unaffected.

unreported tests, we also exclude stocks whose market capitalizations are below the 10^{th} percentile of NYSE stocks, with results unchanged.

In addition to stock returns, we also examine the information embedded in analyst earnings forecasts. In particular, we extract from IBES unadjusted detailed files all available analyst forecasts for the subsequent annual earnings reports. We then compute the monthly forecast revision for each individual analyst based on the last available forecast in each month. If an analyst does not have a valid forecast estimate for the current or the previous month, we treat the revision in that month as missing. Finally, for each firm month, we calculate the consensus analyst forecast revision by taking either the mean or medium forecast revision across all analysts, and standardize it by the lagged stock price.

After applying all screening procedures described above, we end up with a sample of 98,000 distinct firm year observations, among which around 68,000 observations are associated with standalone firms, and the remaining 30,000 are associated with conglomerate firms. Table I shows the summary statistics of our sample. In Panel A, we report the coverage of our sample as a fraction of the CRSP universe. Combined, the standalone and conglomerate firms in the sample cover almost 86% of the CRSP common stock universe in terms of market capitalization, and 78% in terms of the total number of firms. Panel B shows the sample characteristics compared to NYSE stocks. An important feature of conglomerate firms is that they are as big as NYSE stocks with a slight value-tilt. Standalone firms, on the other hand, are significantly smaller than NYSE stocks. This is not surprising given the definition of conglomerate and standalone firms. The average number of industry segments per conglomerate firm is 2.64 (with the median being 2), and an average segment accounts for about 36% of the total sales reported by a conglomerate firm.

4. Results on complicated processing

The main thesis of the paper is that investors have limited resources and capacity to process information, which in turn causes the same piece of information to be impounded into firm values with differential lags. To be more specific, this section examines information events that affect firms within an entire industry. We then exploit the fact that, while it is relatively straightforward to incorporate industry information into a firm operating solely in that industry (i.e., a standalone firm), it generally requires a set of more complicated analyses to impound the same piece of information into the price of a firm that has operating segments in multiple industries (i.e., a conglomerate firm).

4.1 Portfolio tests

We form portfolios to formally test this hypothesis. Specifically, at the end of June in each year, we construct a corresponding "pseudo-conglomerate" for each conglomerate firm in our sample. A "pseudo-conglomerate" is a portfolio of the conglomerate firm's industry segments constructed using solely the standalone firms (easy-to-analyze firms) in each industry; the segment portfolios are then weighted by the percentage of sales contributed by each industry segment within the conglomerate.

Using the example firm from the introduction, CTB, Inc., is a conglomerate firm that makes chocolate, tacos, and light bulbs. Chocolate makes up 40% of CTB's sales, tacos make up 30% of its sales, and light bulbs make up the remaining 30%. CTB's corresponding "pseudo-conglomerate" would then be: 0.4*(a portfolio of all ice cream standalones) + 0.3*(a portfolio of all taco standalones) + 0.3*(a portfolio of all light bulb standalones).

To test our hypothesis that investors' limited information processing capacity can cause delays in information revelation in assets prices, we implement the following strategy. At the beginning of each month (starting in July), using segment information from the previous fiscal year recorded by Compustat, we sort all conglomerate firms into deciles based on the returns of their corresponding pseudo-conglomerate portfolios in the *previous* month. The decile portfolios are then rebalanced at the beginning of each month to maintain either equal or value weights. We refer to this strategy as the *complicated processing* portfolio.

If investors' limited resources and capacity, combined with complications in information processing for conglomerate firms, is truly having an impact on information revelation for these firms, the updating of pseudo-conglomerate values (and corresponding price movements) should then predict the future updating of their paired conglomerate firm values (and thus their future price movements). We test this simple prediction in Table II. As can be seen from Panels A and B, we find strong evidence consistent with complicated information processing affecting the speed at which information is incorporated into prices. Specifically, taking the simple strategy of going long in conglomerate firms whose paired pseudo-conglomerates performed best in the prior month and selling short those conglomerate firms whose pseudo conglomerates performed worse (L/S), yields value-weighted returns of 95 basis points per month (t=3.18), or roughly 11.4% per year. The corresponding equal-weighted returns from the L/S portfolio are 118 basis points per month (t=5.51), or over 14% per year. Controlling for other known return determinants, such as momentum and liquidity, has nearly no effect on these results. For instance, the value-weighted 5-factor alpha of this complicated processing strategy is 104 basis points per month (t=3.01).

In Table III, we examine the factor loadings of the conglomerate portfolio returns formed based on lagged returns of their corresponding pseudo conglomerates. From the last row of Panel B, we see that the value-weight long-short portfolio has no significant loading on any of the 5 factors: the market, size, book-to-market, momentum, or liquidity factor, suggesting that the return predictability pattern we show is distinct from known anomalies in prior literature.

4.2 Transaction costs and net returns

The portfolio returns reported in Tables III and IV are gross returns, without adjusting for transaction costs. In order to get as accurate a picture as possible of the transaction costs involved in trading our strategy, and thus the net returns to the strategy, we obtain historical transaction cost data from a large asset management firm, Nomura International PLC, and calculate the net returns that would have been realized trading the strategy for a number of portfolio sizes.[4]

Based on the data provided by Nomura, transaction costs have a modest effect on our strategy up to a portfolio size of about $10 million. For instance, for a $10 million portfolio (i.e., $10 million on both the long and short sides), net returns to our strategy are roughly 84 basis points per month, t=2.81 (106 basis points per month, t=4.97) on a value-weighted (equal-weighted) basis. However, at a size of $50 million, the effect of transaction costs on the historical returns to the strategy becomes evident. In fact, the value-weighted net returns drop by almost half from 95 to 49 basis points per month, with only marginal statistical significance (t=1.64). Equal-weighted net returns to the strategy also show a large decline to 72 basis points per month, but retain their statistical significance (t=3.38).

4.3 Regression tests

We now test our hypothesis in a regression framework, in which we can better control for other determinants of firm returns and isolate the marginal effect of our main variable, lagged pseudo-conglomerate returns. Specifically, in Table IV, we conduct forecasting regressions of conglomerate returns in the spirit of Fama and MacBeth (1973). The dependent variable in Columns 1-3 is the conglomerate return in month t (RET_t). The independent variable of interest is the return of the conglomerate's paired pseudo-conglomerate in month t-1 ($PCRET_{t-1}$). Other independent variables include the conglomerate's own return in month t-1 (RET_{t-1}) to control for the short term reversal effect of Jegadeesh (1990), and the value-weighted primary industry return of the conglomerate in month t-1 ($INDRET_{t-1}$), as used in Moskowitz and Grinblatt (1999). Lastly, we include additional controls of lagged size, book-to-market, price momentum, and turnover of the given conglomerate firm. Cross

[4] We would like to especially thank Inigo Fraser Jenkins and Dhruv Rastogi from Nomura International PLC for graciously calculating and compiling trading costs for the strategy. Nomura has also calculated trading costs for De Groot, Huij, and Zhou (2010), in which helpful summary statistics can be found.

sectional regressions are run every calendar month and the time-series standard errors are adjusted for heteroskedasticity and autocorrelations up to 12 lags.

The basic results are given in Columns 1 and 2 of Table IV. Consistent with the portfolio results, across both specifications, $PCRET_{t-1}$ is a large and significant predictor of next month's paired conglomerate return. Specifically, after controlling for size, book-to-market, momentum, and turnover, the coefficient on $PCRET_{t-1}$ in Column 1 is 7.408 with a t-statistic of 5.84, indicating that a one-standard-deviation increase in the pseudo-conglomerate return last month leads to a 53 basis point increase in the return of its paired conglomerate firm this month. In Column 2, we further include controls for short-term stock return reversal and industry momentum. These have virtually no effect on the magnitude or significance of $PCRET_{t-1}$.

The analyses reported in Columns 3 and 4 of Table IV are nearly identical to those in Columns 1 and 2, expect that now the dependent variable is the difference between the conglomerate firm return this month and its contemporaneous primary industry return (RET_t - $INDRET_t$), in an effort to better distinguish our return predictability pattern from the previously-known industry momentum effect.[5] In particular, by explicitly purging the conglomerate's return of the contemporaneous primary industry return, we effectively subtract out stock return continuation that arises from industry-wide return autocorrelations. Doing so, we can isolate solely the part of the return predictability that is attributable to delayed information revelation due to the complexity in information processing for conglomerate firms. Column 4 indicates that, even after purging out this industry-wide information, $PCRET_{t-1}$ remains a large and significant predictor of conglomerate returns next month. More specifically, while the coefficient does decrease by about one third, it is still economically large and statistically significant at the one-percent level. Lastly, if we truly are identifying the part of predictable returns for conglomerate firms *solely* attributable to delayed information processing, rather than industry-wide return continuation, we would expect past industry returns to have no predictive power for (RET_t - $INDRET_t$). Consistent

[5] Take the conglomerate firm example, CTB Inc., since chocolate accounts for the largest fraction of its total sales, $INDRET_t$ for CTB is the value-weighted return of the chocolate industry.

with this prediction, the coefficient on past industry returns, $INDRET_{t-1}$, is now indistinguishable from zero.

Columns 5 and 6 of Table IV use an alternative method to purge conglomerate firm returns of contemporaneous industry returns. In particular, the dependent variable in these specifications is the difference between the excess return of a conglomerate firm and that of its paired pseudo-conglomerate in month t (RET_t - $PCRET_t$). This approach addresses one potential concern with the tests reported in Columns 3 and 4. Specifically, one may argue that the value-weighted industry return from Moskowitz and Grinblatt (2001) is an insufficient adjustment for a conglomerate firm's industry exposures, as it only reflects information from the firm's primary industry (e.g., the chocolate industry for CTB Inc.) and excludes all relevant information from its minor sectors (e.g., the taco and light bulb industries). To explicitly rule out this argument that $PCRET_{t-1}$ is simply picking up a finer measure of industry continuation for the conglomerate firms, we subtract from the return of a conglomerate firm the *contemporaneous* return of its corresponding pseudo-conglomerate; which, by construction, encompasses information from all operating segments of the conglomerate firm. In doing so, with (RET_t - $PCRET_t$) we isolate the mechanism of solely complicated information processing causing a delay in information being incorporated into conglomerate firm values, versus any industry-wide return continuation.

Columns 5 and 6 show that $PCRET_{t-1}$ remains a large and significant predictor of its paired conglomerate firm's future return in excess of its own future return (RET_t - $PCRET_t$). This is inconsistent with $PCRET_{t-1}$ being a refined measure of industry returns and our documented return pattern simply reflecting positive autocorrelations in industry-wide factors, but supports our hypothesis that the same industry shocks are incorporated into easy-to-analyze firm values before they are reflected in conglomerate firm values, as the latter require more complicated valuation analyses.[6]

[6] We have also run these same excess return specifications of (RET_t- $INDRET_t$) and (RET_t- $PCRET_t$) in the calendar-time portfolio framework. Similar to the regressions, sorting on the past pseudo-conglomerate return still predicts large, significant spreads in the future excess returns of the more complicated conglomerate firms.

Finally, we also run a number of additional robustness checks to address other potential stories. For instance, Hou (2006) finds a lead-lag relation between weekly returns of large firms and small firms within the same industries. Specifically, Hou (2006) sorts all firms in each industry into three size groups, and finds that firm returns in the largest size group lead returns in the smallest group within the same industry at the weekly horizon. While this prediction runs somewhat counter to what we find, as the average standalone firm is *smaller* than the average conglomerate firm (as seen in Table I) in the sample, it still brings up the possibility of a size-related lead-lag return relation driving our results.[7] In order to explicitly control for this size effect, we follow Hou (2006) to sort firms in every industry into three groups based on size.[8] For every conglomerate firm, we then construct its paired pseudo-conglomerate out of *solely* those standalone firms in the same size group within each of its component industries. In other words, the paired pseudo-conglomerate is now an industry- and size-matched portfolio of standalone firms. We get nearly identical results. For instance, in the analog of the full-specification of Column 2, but now using returns of size-matched pseudo-conglomerates, the coefficient on $PCRET_{t-1}$ is 7.115 (t=6.16). This is even slightly larger in point estimate than that in Column 2 of Table IV, and implies an estimated magnitude of 52 basis points higher conglomerate return in the following month for a one-standard-deviation larger size-matched pseudo-conglomerate return in the previous month.

In addition to employing these size-matched pseudo-conglomerates, we have also included in all our specifications the average market-to-book ratio of each paired pseudo-conglomerate to control for the effect identified in Lamont and Polk (2001). More specifically, Lamont and Polk (2001) find that conglomerate firms with larger discounts (implied by their M/B ratios) have higher expected returns than those with smaller discounts. The coefficient on the average pseudo-conglomerate M/B ratio is

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[7] This may be a potential concern for us given that both *INDRET* and *PCRET* are computed using value weights. One could therefore argue that we are essentially using large standalones to form our pseudo conglomerate portfolios.

[8] Note also that all of our tests up to this point have been at the lower frequency of monthly return predictability based on last month's pseudo-conglomerate returns. We show in Table IX the evolution of complicated information processing effect at the weekly frequency, as well.

small and insignificant in all specifications, and has virtually no impact on the coefficient of past pseudo-conglomerate returns. For instance, in the analog of the full-specification of Column 2, the coefficient on the average pseudo-conglomerate M/B ratio is 0.162 (t=0.83), while the coefficient on $PCRET_{t-1}$ is 6.923 (t=6.72).

In sum, the portfolio and regression results provided in this section suggest that complicated information processing required by conglomerate firms causes a substantial delay in industry-wide information being impounded into their prices. Such a delay in turn gives rise to significant predictable returns of conglomerate firms from their corresponding standalones, whose values more promptly reflect important industry information. The regression results, in particular, lend strong support to our hypothesis that the robust return predictability pattern we document is *not* driven by other know return determinants, nor is it due to industry return continuation, but instead caused by investors' limited information processing capacity combined with complicated valuation analyses required by conglomerate firms relative to their simple standalone counterparts.

5. Mechanism

5.1 More complicated firms

In this section, we examine the mechanism of complicated information processing affecting the price updating of conglomerate firms in more depth. We begin by examining conglomerate firms that are especially complicated to value. If our return effect is truly driven by investors' limited capacity and resources, combined with the valuation difficulty of conglomerate firms, we would expect that the more complicated the firm, the more severe the lag in incorporating information into prices, and thus the stronger the return predictability. To test this prediction, we create a measure of how complicated a conglomerate firm is using a Herfindahl index based on the firm's segment sales. For example, the Herfindahl index for the conglomerate firm in the previous section that operates in the chocolate, taco, and light bulb industries, CTB, is defined as $(.4)^2+(.3)^2+(.3)^2=0.34$. The idea behind this measure is that, the more dispersed a firm's operations across its industry segments, the more complicated the analyses needed to incorporate a given piece of information into its price.[9] We then create a categorical variable that equals one if a conglomerate firm is above the sample median in a given year in terms of this Herfindahl measure, and zero otherwise. The prediction is thus that the coefficient on the interaction term of $PCRET_{t-1}$ with this categorical variable be negative, i.e., these firms requiring less complicated information processing should have less severe return predictability.

The results of the test are reported in Column 1 of Table V. The regression specification is similar to those in Table IV, i.e., a Fama-MacBeth predictive regression with the dependent variable being the conglomerate firm return (RET_t) in the following month. In addition to the interaction term between the categorical variable and $PCRET_{t-1}$, the categorical variable itself along with all control variables from the full specification (Table IV, Column 2) are also included, which are unreported for brevity. We observe from Column 1 that the coefficient estimate on the interaction term between an indicator of less complicated firms and past pseudo-conglomerate's return ($PCRET_{t-1}$) is negative and statistically significant, -3.458 (t=-3.33). For comparison, the unconditional coefficient on $PCRET_{t-1}$ from Table IV is 6.896. Thus, consistent with the complexity of conglomerate firms driving the return predictability pattern, firms that are relatively less complicated, and so require simpler processing to incorporate information about any single segment into prices, exhibit less pronounced predictable returns.

5.2 Difficult-to-arbitrage firms

Even if a subset of investors are severely constrained in their information processing capacity, and therefore can cause a delay in information revelation in a set of complex-to-analyze firms, the less constrained investors (e.g., professional money managers) should take advantage of the return predictability and arbitrage away part of

[9] We have also used the number of industry segments within a conglomerate firm as an alternative measure, and get similar results. We prefer the Herfindahl index as it captures the actual concentration of firm operations, as opposed to a simple count of industry segments. For example, consider a second conglomerate firm, CTB2, that also operates in the chocolate, taco, and light bulb industries, but receives 90% of its total revenue from the chocolate industry. Although it has three operating segments, it is actually closer to a standalone firm.

the predictable abnormal returns. An immediate prediction of this argument is that, for stocks with more binding limits to arbitrage, we should see a stronger return effect, as more sophisticated investors are less able (or willing) to fully update these firms' prices. We employ two variables that are commonly used in the literature to capture limits to arbitrage in the stock market: idiosyncratic volatility and firm size. While we are not claiming these are perfect proxies, we do believe, especially in the case of idiosyncratic volatility, that these proxies are likely correlated with classic limits to arbitrage, such as the ability to retain positions (capital) in the face of prices moving (temporarily) further away from fundamental values.

To test this prediction, we construct two categorical variables that equal one if the firm is above the sample median in terms of idiosyncratic volatility and market capitalization, respectively, and zero otherwise. As shown in Column 2 of Table V, the coefficient estimate on the interaction term between the idiosyncratic volatility dummy and $PCRET_{t-1}$ is large and statistically significant, 3.159 (t=2.43), which implies that the magnitude of the documented return effect is over 50% larger for stocks with high idiosyncratic volatility relative to those with low idiosyncratic volatility. This is consistent with our prediction that firms that are more likely to have large temporary price swings, and are thus less attractive to arbitrage capital, should exhibit a stronger return effect. In the same vein, Column 3 shows that, while the complicated-information-processing return effect among large conglomerate firms is strong and significant, the effect in small firms is even larger. Both of these findings lend support to our prediction that complications in information processing have an even larger impact on difficult-to-arbitrage stocks.

5.3 Investors' inattention

In the final three columns of Table V, we test whether our results are entirely driven by an investors' inattention explanation, i.e., that investors are unaware of a piece of information and/or a particular stock. While this seems unlikely, given that the industry-wide information we are identifying has already entered first into the values of smaller standalones firms, we still employ some common proxies for (in)attention to test this more formally. Specifically, if investors' limited attention plays a significant role here, we would expect stronger return predictability for conglomerate firms that attract less investor attention. We use three common proxies for inattention in the literature: lower institutional investor ownership, lower turnover, and lower analyst coverage. Note that institutional ownership here is the residual institutional ownership after being orthogonalized with respect to firm size.

The results are reported in Columns 4 to 6. All three interaction terms are insignificant and small in magnitude, with the coefficient on turnover even being in the wrong direction. This lends further support to our hypothesis that the return effect is driven by complications in the processing of information for conglomerate firms, and not simply by investors ignoring this underlying information and/or the underlying stocks.

5.4 Change of firm status

In this section, we perform a cleaner test of the mechanism of complicated information processing affecting firm values, by examining a particular setting where we can follow the *same* firm as both a standalone and a conglomerate. Specifically, we restrict our analysis to solely those standalone firms that transition to conglomerate firms, through, for example, mergers and acquisitions, and initializing new business lines.[10] Although this rather restrictive setting results in many fewer firms, the advantage of this test is that we can now examine the time lags in information updating of the exact *same* firm when it requires easy as opposed to complicated information processing.

The prediction is that, when the same firm operates in multiple segments, its corresponding pseudo-conglomerate should be a significant and positive predictor of its future price movements (after controlling for all other known return determinants and industry-wide return continuation). When it is a standalone firm, however, the analogous pseudo-conglomerate portfolio, which is now simply a portfolio of all *other*

[10] We have examined the opposite case as well, i.e., conglomerate firms transition to standalones through divestiture, but empirically in the majority of these cases the conglomerate firm actually keeps a portion of the unit (and its facilities), and yet stops reporting the segment's financial information separately.

standalones in the same industry, should have relatively weaker (or insignificant) predictability over its future returns.

We implement this test by first identifying all cases in which a standalone firm transitions into a conglomerate firm.[11] We then include observations within three years prior to the status change in the standalone-status sample, and those within three years subsequent to the status change in the conglomerate-status sample. We conduct Fama-MacBeth return predictive regressions, similar to those in Table IV, on both samples. The results are reported in Table VI. Comparing Columns 2 and 4 (with a stricter specification where the dependent variable is RET_t-$PCRET_t$), we observe that $PCRET_{t-1}$ has no predictability over excess returns when a firm is a standalone (0.581, t=1.08), but, in contrast, has significant return predictability when the *same* firm is a more complicated conglomerate firm (3.206, t=2.71). The difference between these two coefficients of 2.626 is significant at the 5% level (t=2.12).[12] Also, note that the coefficients on $PCRET_{t-1}$ in Columns 3 and 4 (when the given firm is a conglomerate) are quite similar to those based on the universe of conglomerate firms, reported in Columns 1 and 5 of Table IV, respectively. This suggests that there is nothing unusual about these conglomerate firms that have recently changed status, relative to all other conglomerates, in terms of complications in information processing.

5.5 Analyst information updating in complicated firms

All the results we have presented to this point are consistent with two interpretations. The first interpretation, which we focus on in this paper, is a complicated information processing mechanism, in which investors have limited capacity to assess how a given piece of industry-specific information can affect a complicated firm's value that comprises of a number of industry segments, each with a distinct yet

[11] We exclude all such cases in years 1998 and 1999, which are likely due to a significant change in reporting requirements corresponding to the introduction of SFAS No. 131, which superseded No. 14.

[12] Columns 1 and 3 show that, while there is some autocorrelation in standalone firm returns (from Column 1), the same result holds. The difference of 3.570 between Columns 1 and 3 is statistically significant (t=2.22). This suggests that the same firm's future price movements are significantly more related to the past pseudo-conglomerate returns when it is a complicated conglomerate firm, as opposed to a simple standalone firm.

unknown weight. The second explanation is a complicated trading channel, where even if investors knew the exact weights of individual segments, and how a given piece of information about a single segment would affect the complicated firm's value, it might still be difficult for them to undertake the complex set of trades needed to get this information into prices. For instance, consider again the three segment conglomerate firm CTB, Inc. If information arrives about one of the industries (e.g., chocolate), in the absence of information about the other two segments, and given that one does not want to bear the information risk of these other segments, one would have to long the conglomerate firm, and then put on a series of trades to hedge out the risk of the other two segments.

While it could certainly be that both explanations, complicated information processing and complicated trading, are present in driving these price patterns, in this section, we present a test that helps distinguish between the two. Specifically, we examine the behavior of sell-side analysts who usually cover both simple- and complicated-to-analyze firms. On the one hand, analysts are constrained to only issue forecasts for an entire firm rather than its individual segments, and thus face the same complexity as an average investor in incorporating information about a single segment into conglomerate firm values. On the other hand, since analysts do not have to undertake any hedging trades in their forecasts, they are completely free of the complicated trading friction. Thus, if it is mainly the complicated information processing mechanism that is driving our results, we would expect to see a similar predictive pattern in analyst forecasts between simple standalone and complicated conglomerate firms, assuming that analysts also have limited information processing capacity. On the flip side, if it is the complicated trading channel that is driving our results, we should see no such effect in analyst behavior.

We test these predictions using sell-side analysts' annual earnings forecasts, as these forecasts are updated most frequently and thus afford us the most statistical power. We conduct a regression analysis that is almost identical to those performed in Table IV expect that, instead of using stock returns, we focus on monthly revisions in consensus forecasts for the subsequent annual earnings announcements. Thus, we test whether analysts' forecast revisions for simple standalones firms, which we now aggregate into a measure labeled the pseudo-conglomerate forecast (PCF_{t-1}), predict future forecast revisions of their corresponding complicated conglomerate firms (F_t).

The tests are shown in Table VII. The results imply that analysts are affected by similar information processing complications as investors and thus update their forecasts for simple standalone firms before these more complicated conglomerate firms. Specifically, Columns 1 and 2 show positive and significant coefficients on past pseudo-conglomerate forecast revisions (PCF_{t-1}) in predicting future forecast revisions of their paired conglomerate firms. In Column 2, after controlling for the well-known autocorrelation in analyst forecast revisions, the coefficient of 5.370 (t=2.51) on PCF_{t-1} implies a 15% more positive annual earnings forecast revision for a conglomerate firm following a one-standard-deviation increase in the forecast revision of the paired pseudo-conglomerate portfolio in the previous month. Interestingly, Column 3 shows that this predictability does not flow in the opposite direction, as past conglomerate firms' forecast revisions (F_{t-1}) contain no additional information for the future earnings forecasts revisions of their paired standalones. Combined, these results provide evidence that the return predictability pattern we document in this paper is more consistent with the complicated-information-processing channel, and less so with complications in trading.

One potential issue with the tests conducted in Table VII is that the average forecast revision of a portfolio, PCF_{t-1}, is a less noisy measure of industry information than the forecast revision of a single firm, F_{t-1}, which naturally contains more idiosyncratic earnings information. If there is a positive autocorrelation in industry-wide earnings news, we would then expect PCF_{t-1} to be a stronger predictor than F_{t-1} of future industry earnings forecast revisions. Put differently, the results in Table VII may be simply reflecting an industry-wide positive autocorrelation in earnings information.

To test whether the noisiness of F_{t-1} vs. PCF_{t-1} is driving our result, we perform the following test. We randomly assign all standalone firms in each industry into two equally sized groups (Group 1 and Group 2). We then test whether the previous-month forecast revision of the Group 1 pseudo-conglomerate (PCF^1_{t-1}) predicts the following-month forecast revision of its paired conglomerate above and beyond the subsequent revision of the Group 2 pseudo-conglomerate (F_t - PCF^2_t). The reason we split standalone firms into two groups is to alleviate the well-established within-firm autocorrelation in forecast revisions. This measuring of the impact of PCF^1_{t-1} on (F_t - PCF^2_t) is similar in interpretation to estimating the impact of $PCRET_{t-1}$ on (RET_t - $PCRET_t$), from Table IV.

If we are simply picking up a general autocorrelation in industry-wide forecast revisions, PCF^1_{t-1} should no longer have predictive power for (F_t - PCF^2_t). On the other hand, if analysts tend to update their earnings forecasts for standalone firms before conglomerate firms, as the latter require more complicated analyses, we would expect PCF^1_{t-1} to positively and significantly predict (F_t - PCF^2_t). The results are consistent with the complicated-information-processing hypothesis. The coefficient on PCF^1_{t-1} in this specification is 5.833 (t=2.52), nearly identical to that in Column 2 of Table VII.[13] In sum, the results presented in this subsection indicate a systematic pattern of forecast revisions of standalone firms predicting future forecast revisions of their more complicated conglomerate counterparts, due to complications in information processing for the latter.

6. Sentiment and categorical thinking

While the paper up to this point has focused on the complicated nature of conglomerate firms affecting information processing, we now switch focus to the potential impacts of this same complication on transmission of non-fundamental shocks. Specifically, we build upon the evidence on categorical thinking, and the observation that sentiment often acts at the level of categories (Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005)).[14] The idea is that if the complication this paper identifies is also a friction to categorization, it could have implications for the impact of sentiment on complicated vs. simple-to-analyze firms.

[13] Since we split all standalone firms in each industry randomly into two groups, the coefficient on PCF^1_{t-1} is calculated as the average coefficient from five hundred iterations of random sampling.

[14] See Baker and Wurgler (2007) for a comprehensive survey of the sentiment literature.

For example, when people are excited about software (unrelated to fundamentals), they may immediately think of the simple focused firms in software, and purchase these stocks, driving their prices away from fundamental value and causing eventual return reversals. On the other hand, investors are unable to categorize complicated conglomerate firms that operate in software and many other industries, and so these complicated firms are less subject to these sentiment shocks and the resultant return effects from sentiment.

6.1 Sentiment test

Given that the friction we identify throughout the paper is about the differential incorporation of industry level information into both complicated and easy to analyze firms, we further examine the impact of this same complication on the transmission of non-fundamental shocks. Specifically, building upon prior research on categorical thinking, we test whether the complication in information processing is also a friction to categorization. That is, if complicated firms are more difficult to categorize, we expect that sentiment-related return shocks affect simple-to-analyze firms to a larger extent than complicated-to-analyze firms.

Prior literature on sentiment suggests four measures that might ex-ante be expected to aggregate and be expressed at the industry level: i.) net equity issuance, ii.) B/M, iii.) 5-year past return, and iv.) retail investor demand. We examine these measures one by one. First, while net equity issuance seems to work well at many aggregation levels, Greenwood and Hanson (2010) find fairly weak evidence at the industry level (and we replicate this). Second, for industry B/M, Cohen and Polk (1996) show that industry average B/M ratios do not have predictability for future returns of the industry constituents, which we also replicate. Third, in terms of the 5-year past return, it is, to some degree, correlated with B/M. Like the B/M ratio, this measure does not have predictive power for future returns when aggregated at the industry level.

In contrast to these three measures, Jame and Tong (2009) show that retail investor demand aggregated to the industry level has a strong negative relation with future industry returns. Specifically, they show that retail investors herd at the industry level, and that future industry returns are negatively related to the amount and sign (buy or sell) of retail investor trading in that industry. We replicate their result, and consequently use aggregate retail investor demand as our measure of sentiment in each industry.[15]

The sentiment test we run is almost identical to that reported in Table IV, with the only difference being that we are now testing how these industry sentiment measures relate with future returns. The main variable of interest -- the retail investor sentiment of the pseudo-conglomerate, $PCIMBL_{t-1}$ -- measures the aggregate sentiment shocks for the conglomerate firm's component industries.[16]

The results are shown in Table VIII. First, in Columns 2 and 3 of Panel A, similar to the results shown in Barber, Odean, and Zhu (2008) and Hvidkjaer (2008), we find that the firm-level retail investor order imbalances ($IMBL_{t-1}$) are negatively related to future returns. From Column 1, the industry-level sentiment measure ($PCIMBL_{t-1}$) is a negative predictor (as in Jame and Tong (2009)) for future pseudo-conglomerate returns (-0.090, t=1.81). In contrast, from Column 2 it has no predictive power for future *conglomerate* returns. In fact, Column 3 shows the differential relations of industry sentiment to the future returns of simple to categorize, as opposed to complicated to categorize firms, is statistically significant (0.113, t=2.08). This magnitude implies that a one standard deviation increase in industry sentiment leads to a roughly 11 basis point lower return of simple to categorize, relative to complicated to categorize, firms in the following month.

[15] A nice aspect of the sentiment measure is that it's constructed from investor trading, and not a direct return-based measure, which is used throughout the rest of the paper (and thus the sentiment measure may be capturing a different mechanism).

[16] We use tick-by-tick transition data compiled by the Institute for the Study of Securities Market (ISSM) for the period 1983 to 1992 and New York Stock Exchange (NYSE TAQ) for the period of 1993 to 2000. Following Barber, Odean and Zhu (2008), we classify trades that are below $5000 in size as small trades, which are likely submitted by retail investors. We identify each trade as buyer- or seller-initiated following the procedure outlined in Lee and Ready (1991). In each month, we count the number of buyer-initiated small trades (#SmallBuys) and the number of seller-initiated small trades (#SmallSells), and define our mean measure, $Imbal_{i,t}$, as (#SmallBuys - #SmallSells) / (#SmallBuys + #SmallSells). For robustness, we also construct our *Imbal* measure based on the number of shares bought and sold by retail investors in each month. Lastly, we also compute a measure of annual *Imbal*, which is the sum of monthly *Imbal* over the past 12 months.

The other important aspect of this sentiment story is that the sentiment moves prices away from fundamental value in the first place (to then cause the reversals we show above). This is precisely what we show in Panel B of Table VIII. Contemporaneous with the industry sentiment ($PCIMBL_t$), we document significant price pressure and positive returns for simple to categorize firms (from Column 1, 1.233, t=2.53), and yet no such price movement for difficult to categorize firms (Column 2 of Panel B). Again, from Column 3, the difference between the simple and complicated firms' contemporaneous price movements due to sentiment is statistically significant.

In sum, the previous sections of our paper show that complicated firms are subject to the same industry *information* shocks (as we would expect), and so update to this important industry information, albeit with a substantive lag. However, a different pattern emerges for sentiment shocks. We find that difficult to categorize firms are not subject to the shift away from fundamental value due to sentiment, nor do they experience the subsequent reversal back to fundamental value. This is consistent with frictions to categorization (i.e., being a conglomerate firm) preventing complicated firms from being categorized, and thus from being subject to the same sentiment shocks as easy to categorize firms.

7. Robustness checks and return horizon

7.1 Robustness checks

We perform a number of additional specification and robustness checks on our results. First, we show that our return predictability pattern remains economically and statistically significant using a different benchmark of expected returns. Specifically, we calculate characteristic-adjusted returns following Daniel et al. (1997). Using the same portfolio procedure described in Table II, and characteristics-based adjustments for all conglomerate firms, we report the resulting excess returns in Table IX. Characteristic-adjusted returns remain large and significant: the equal-weighted portfolio yields 84 basis points (t=5.34), while the value-weighted portfolio returning 72 basis points (t=3.34) per month. The return effect is also robust to a number of ways of splitting the sample; it remains economically important and statistically significant across large and small firms, and in low and high idiosyncratic volatility firms (with the exception of the value-weighted low idiosyncratic volatility firm sample, where the returns are still 44 basis points a month, but statistically insignificant).[17] We also experiment with a different weighting scheme in the construction of pseudo-conglomerate portfolios: rather than weight each industry segment based on the segment sales as a percentage of the total conglomerate sales, we weight by the segment assets as a percentage of the total assets. The results are by and large unchanged, indicating that the return predictability pattern we identify is robust to alternative measures of relative weights of industry segments.

7.2 Horizon of complicated processing return effect

To gain a better understanding of the return pattern resulting from complicated information processing, we next examine the horizon of the return effect in two ways. First, we dissect the *monthly* return predictability pattern that we have documented up to this point into more refined *weekly* return effects. Second, we explore cumulative return responses of conglomerate firms over an extended horizon.

To explore the week-by-week evolution of return predictability, we directly borrow the regression specification from Table IV, except that now we dissect the monthly return predictability of the pseudo-conglomerate into each of the following four weeks of *RET*. So, $PCRET_{t-3}$, for instance, measures the impact of the monthly (i.e., four-week cumulative) pseudo-conglomerate return on the weekly return of its paired conglomerate three weeks later. We then include all of the other control variables from Table IV, which are unreported for brevity.

The results are shown in Table X. We observe that lagged pseudo-conglomerate returns have strong predictive power for their corresponding conglomerate firm returns in all four weeks of the following month. Interestingly, the impact of the information

[17] Note that we are choosing to split sub-samples here on some of the same variables we use in Table V. This is intentional, as while we show in the regressions there that these characteristics can *moderate* this complicated information processing effect on returns (which is borne out also in portfolios), we wanted to show clearly here that the complicated information processing effect was present across these characteristic sub-samples.

contained in pseudo-conglomerate price movements on subsequent conglomerate returns is monotonically decreasing across the weeks, from the most recent week (2.558, t=7.29) to four weeks prior (1.019, t=4.53). This is consistent with the idea that, as investors are availed of more time to process the information, more of the information is reflected in the prices of conglomerate firms.[18]

Finally, we also examine the long-run return pattern of this complicated information processing effect. This is mainly to examine whether the strong and positive return effect we show is some form of overreaction in conglomerate firm values, in which case we would expect to see a full reversal in the longer term. In contrast, if we are instead documenting the delayed updating of conglomerate firms to information truly important to their fundamental values, we should see no reversal following their delayed updating.

To test between these two alternative stories, we simply examine the cumulative returns to the portfolio strategy described in Table II over the longer term. We show these long-run cumulative returns in Figure 2, with both equal- and value-weighted results. The large month 1 returns in Figure 2 correspond to the portfolio returns from Table II. We then observe modest additional upward drift through month 6. More importantly, we see no sign of any return reversal. Extending the horizon to 12 (or 24) months produces largely the same results, as the return pattern flattens at months 7 to 8, and remains flat thereafter. The important conclusion from this figure is that we see no reversal of the return effects we document over the long-run, suggesting that we truly are capturing a mechanism of delayed updating of conglomerate firm prices to information important to their fundamental values.

8. Conclusion

We explore a new mechanism by which asset prices are sensitive to the complexity of information processing. We use a novel approach, that of identifying two sets of firms that require easy vs. complicated analyses to reflect the *same* piece of

[18] In addition, as we might expect, adding up the coefficients of the four past weeks gives roughly the same magnitude as the coefficient on past month pseudo-conglomerate return from Table IV.

information. Specifically, we look at industry-wide information events, and exploit the fact that, while it is straightforward to incorporate industry-specific information into a firm operating solely in that industry (i.e., standalone firms), it generally requires more complicated analyses to incorporate the same piece of information into the price of a firm with operating segments in multiple industries (i.e., conglomerate firms). We find strong evidence that easy-to-analyze firms incorporate industry information first, and hence their returns strongly predict the future updating of firm values that require more complicated analyses. Consistent with processing complexity driving the return relation, we further show that, the more complicated the firm, the more pronounced the return predictability. In addition, sell-side analysts exhibit these same information processing constraints, as their forecast revisions of easy-to-analyze standalone firms significantly predict the future forecast revisions of more complicated conglomerate firms. Interestingly, these complicated firms also appear to be more difficult for investors to categorize, and being so, they do not experience the shift away from fundamental value due to industry sentiment shocks, nor do they experience the subsequent reversal back to fundamental value.

A portfolio that takes advantage of this return predictability yields significant returns – ranging from 11.4%-14% a year. These returns are virtually unrelated to previously known return determinants, robust to different specifications, across various subsets of firms, and exhibit no return reversal in the long-run. Understanding how the mechanism of complicated information processing, and how frictions to processing information more generally, can affect information updating, will give us a richer picture of how information is revealed into prices across the universe of firms, and so a deeper understanding of what drives asset prices.

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Table I: Summary statistics, 1977–2009

This table shows summary statistics as of December of each year. Percent coverage of stock universe (EW) is the number of stocks either included in the conglomerate or standalone sample for a given year divided by the total number of CRSP stocks. Percent coverage of stock universe (VW) is the total market capitalization of stocks included in the conglomerate or standalone sample for the given year, divided by the total market value of the CRSP stock universe. Size is the firm's market value of equity. Book to market is the Compustat book value of equity divided by the market value of equity. Market capitalization percentile and book to market percentile are measured based on the NYSE sample.

	Min	Median	Max	Mean	Std Dev
Panel A: Time series (33 annual observations, 1977 – 2009)					
Number of conglm firms in the sample per year	542	840	1288	898	198
Number of standalones in the sample per year	919	1948	3563	2069	632
Full sample % coverage of CRSP universe (EW)	51.39	79.04	86.02	77.53	6.78
Full sample % coverage of CRSP universe (VW)	61.24	89.82	93.26	85.69	7.41
Conglm firms % of CRSP universe (EW)	15.44	21.93	37.54	24.04	6.39
Conglm firms % of CRSP universe (VW)	32.07	43.90	57.20	44.56	6.19
Standalones % of CRSP universe (EW)	26.03	53.10	70.37	53.49	8.96
Standalones % of CRSP universe (VW)	29.17	40.31	54.98	41.13	6.51
Panel B: Firms (Pooled firm–year observations)					
Conglm firm market-cap percentile (NYSE)	0.00	0.51	1.00	0.50	0.32
Standalone market-cap percentile (NYSE)	0.00	0.30	1.00	0.36	0.28
Conglm firm book-to-market percentile (NYSE)	0.00	0.65	1.00	0.60	0.27
Standalone book-to-market percentile (NYSE)	0.00	0.55	1.00	0.51	0.29
# of industries per conglomerate	2	2	10	2.64	0.94
Percent of sales per industry segment	0	0.27	1	0.36	0.29

Table II: Complicated Processing Portfolios, abnormal returns 1977–2009

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month, all conglomerate stocks are ranked in ascending order on the basis of the returns of their corresponding pseudo-conglomerates in the previous month. A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The ranked stocks are assigned to one of 10 decile portfolios. All stocks are value (equally) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights. This table includes all available stocks with stock price greater than $5 at portfolio formation. Alpha is the intercept on a regression of monthly excess return from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. L/S is the alpha of a zero-cost portfolio of conglomerate firms that holds the firms with the top 10% pseudo-conglomerate returns and sells short the firms with the bottom 10% pseudo-conglomerate returns in the previous month. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Equal weights					
Decile	Excess Returns	1-factor alpha	3-factor alpha	4-factor alpha	5-factor alpha
1	0.14%	-0.47%	-0.71%	-0.61%	-0.65%
(low)	(0.43)	(-2.83)	(-4.80)	(-4.01)	(-4.39)
2	0.08%	-0.50%	-0.73%	-0.64%	-0.68%
	(0.28)	(-3.57)	(-5.94)	(-5.35)	(-5.90)
3	0.50%	-0.03%	-0.25%	-0.18%	-0.20%
	(1.85)	(-0.25)	(-2.30)	(-1.63)	(-1.85)
4	0.67%	0.14%	-0.09%	0.00%	-0.01%
	(2.48)	(1.11)	(-0.82)	(0.01)	(-0.09)
5	0.85%	0.34%	0.11%	0.18%	0.19%
	(3.26)	(2.83)	(1.16)	(1.90)	(1.96)
6	0.85%	0.32%	0.08%	0.15%	0.15%
	(3.20)	(2.72)	(0.84)	(1.54)	(1.50)
7	0.90%	0.37%	0.13%	0.15%	0.16%
	(3.38)	(3.11)	(1.36)	(1.43)	(1.57)
8	0.97%	0.44%	0.21%	0.22%	0.24%
	(3.63)	(3.67)	(2.15)	(2.00)	(2.20)
9	0.99%	0.46%	0.24%	0.24%	0.25%
	(3.66)	(3.61)	(2.23)	(2.12)	(2.12)
10	1.31%	0.74%	0.48%	0.47%	0.47%
(high)	(4.34)	(4.63)	(3.63)	(3.30)	(3.09)
L/S	**1.18%**	**1.21%**	**1.18%**	**1.08%**	**1.12%**
	(5.51)	(5.52)	(5.30)	(4.48)	(4.50)

Table II: Complicated Processing Portfolios (continued)

Panel B: Value weights					
Decile	Excess Returns	1-factor alpha	3-factor alpha	4-factor alpha	5-factor alpha
1	-0.10%	-0.69%	-0.78%	-0.68%	-0.77%
(low)	(-0.29)	(-3.42)	(-3.65)	(-2.91)	(-3.35)
2	0.19%	-0.33%	-0.39%	-0.32%	-0.36%
	(0.68)	(-2.31)	(-2.74)	(-2.25)	(-2.55)
3	0.39%	-0.11%	-0.16%	-0.13%	-0.14%
	(1.45)	(-0.75)	(-1.07)	(-0.80)	(-0.87)
4	0.43%	-0.06%	-0.10%	-0.08%	-0.09%
	(1.69)	(-0.42)	(-0.75)	(-0.55)	(-0.62)
5	0.54%	0.06%	0.04%	0.06%	0.08%
	(2.14)	(0.44)	(0.34)	(0.47)	(0.57)
6	0.78%	0.28%	0.21%	0.24%	0.28%
	(3.02)	(2.32)	(1.81)	(1.74)	(2.16)
7	0.64%	0.17%	0.12%	0.07%	0.10%
	(2.59)	(1.36)	(0.93)	(0.53)	(0.75)
8	0.77%	0.28%	0.25%	0.15%	0.24%
	(2.94)	(1.97)	(1.67)	(0.99)	(1.67)
9	0.78%	0.28%	0.18%	0.21%	0.25%
	(2.84)	(1.75)	(1.19)	(1.37)	(1.62)
10	0.85%	0.32%	0.25%	0.28%	0.27%
(high)	(2.83)	(1.74)	(1.37)	(1.54)	(1.41)
L/S	**0.95%**	**1.01%**	**1.03%**	**0.97%**	**1.04%**
	(3.18)	(3.35)	(3.32)	(2.85)	(3.01)

Table III: Complicated Processing Portfolios, factor loadings 1977–2009

This table shows calendar time portfolio factor loadings. At the beginning of every calendar month, all conglomerate stocks are ranked in ascending order on the basis of the returns of their corresponding pseudo-conglomerates in the previous month. A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The ranked stocks are assigned to one of 10 decile portfolios. All stocks are value (equally) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights. This table includes all available stocks with stock price greater than $5 at portfolio formation. Alpha is the intercept on a regression of monthly excess return from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. L/S is the alpha of a zero-cost portfolio of conglomerate firms that holds the firms with the top 10% pseudo-conglomerate returns and sells short the firms with the bottom 10% pseudo-conglomerate returns in the previous month. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Equal weights							
	xret	alpha	MKT	SMB	HML	UMD	LIQ
1	0.14%	-0.65%	1.156	0.511	0.297	-0.109	0.074
(low)	(0.43)	(-4.39)	(28.85)	(5.37)	(3.70)	(-2.01)	(1.67)
2	0.08%	-0.68%	1.126	0.412	0.324	-0.098	0.064
	(0.28)	(-5.90)	(35.06)	(4.88)	(4.43)	(-2.34)	(1.64)
3	0.50%	-0.20%	1.036	0.409	0.305	-0.083	0.030
	(1.85)	(-1.85)	(36.00)	(6.14)	(4.86)	(-2.35)	(0.80)
4	0.67%	-0.01%	1.027	0.416	0.298	-0.095	0.018
	(2.48)	(-0.09)	(38.02)	(6.83)	(5.09)	(-2.21)	(0.54)
5	0.85%	0.19%	0.998	0.415	0.311	-0.074	-0.012
	(3.26)	(1.96)	(42.42)	(9.20)	(6.15)	(-2.71)	(-0.36)
6	0.85%	0.15%	1.032	0.415	0.343	-0.074	0.003
	(3.20)	(1.50)	(34.45)	(8.62)	(7.13)	(-2.48)	(0.10)
7	0.90%	0.16%	1.040	0.445	0.356	-0.020	-0.020
	(3.38)	(1.57)	(36.06)	(9.48)	(6.82)	(-0.68)	(-0.51)
8	0.97%	0.24%	1.039	0.419	0.345	-0.009	-0.036
	(3.63)	(2.20)	(40.35)	(8.21)	(6.97)	(-0.21)	(-1.01)
9	0.99%	0.25%	1.057	0.379	0.335	-0.008	-0.013
	(3.66)	(2.12)	(29.21)	(6.24)	(5.78)	(-0.19)	(-0.41)
10	1.31%	0.47%	1.123	0.524	0.391	0.004	0.006
(high)	(4.34)	(3.09)	(28.86)	(8.10)	(5.65)	(0.06)	(0.15)
L/S	**1.18%**	**1.12%**	-0.033	0.013	0.094	0.113	-0.068
	(5.51)	(4.50)	(-0.51)	(0.10)	(0.73)	(1.05)	(-0.94)

Table III: Complicated Processing, factor loadings (continued)

Panel B: Value weights							
	xret	alpha	MKT	SMB	HML	UMD	LIQ
1	-0.10%	-0.76%	1.182	0.020	0.155	-0.105	0.135
(low)	(-0.29)	(-3.35)	(22.12)	(0.19)	(1.52)	(-1.33)	(2.14)
2	0.19%	-0.36%	1.032	-0.017	0.092	-0.077	0.066
	(0.68)	(-2.55)	(30.04)	(-0.33)	(1.10)	(-1.77)	(1.48)
3	0.39%	-0.14%	0.979	0.031	0.083	-0.034	0.022
	(1.45)	(-0.87)	(25.10)	(0.45)	(1.10)	(-0.59)	(0.54)
4	0.43%	-0.09%	0.974	-0.074	0.105	-0.023	0.018
	(1.69)	(-0.62)	(27.93)	(-1.41)	(1.59)	(-0.45)	(0.39)
5	0.54%	0.08%	0.995	-0.209	0.090	-0.020	-0.025
	(2.14)	(0.57)	(32.68)	(-3.75)	(1.66)	(-0.62)	(-0.65)
6	0.78%	0.28%	1.048	-0.188	0.193	-0.030	-0.070
	(3.02)	(2.16)	(30.03)	(-3.67)	(3.23)	(-0.55)	(-1.68)
7	0.64%	0.10%	0.982	-0.142	0.171	0.055	-0.044
	(2.59)	(0.75)	(28.89)	(-2.02)	(3.10)	(1.38)	(-0.96)
8	0.77%	0.24%	1.034	-0.240	0.189	0.108	-0.146
	(2.94)	(1.67)	(26.56)	(-3.83)	(2.78)	(2.70)	(-3.32)
9	0.78%	0.25%	1.024	-0.023	0.191	-0.028	-0.066
	(2.84)	(1.62)	(23.82)	(-0.27)	(2.15)	(-0.49)	(-1.42)
10	0.85%	0.27%	1.058	0.008	0.138	-0.032	0.018
(high)	(2.83)	(1.41)	(19.58)	(0.08)	(1.50)	(-0.54)	(0.34)
L/S	**0.95%**	**1.04%**	-0.124	-0.012	-0.018	0.073	-0.117
	(3.18)	(3.01)	(-1.40)	(-0.07)	(-0.11)	(0.61)	(-1.30)

Table IV: Complicated Processing Returns, cross sectional regressions 1977–2009

This table reports Fama-MacBeth forecasting regressions of stock returns. The dependent variable in columns 1 and 2 is the monthly return of the conglomerate (*RET*), in columns 3 and 4 is the excess conglomerate return over its value-weighted industry return (*RET-INDRET*), while in columns 5 and 6 the dependent variable is the excess return of the conglomerate over its paired pseudo-conglomerate (*RET-PCRET*). A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The explanatory variables are the lagged pseudo-conglomerate return (*PCRET*), the firm's own lagged return (*RET*), and lagged return of the corresponding industry portfolio to the conglomerate's principal industry (*INDRET*). All regressions also include *SIZE*, *B/M*, *MOM*, and *TURNOVER*, all of which are measured at the end of June of each year. Cross sectional regressions are run every calendar month and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

Dep Variable	RET_t		RET_t - $INDRET_t$		$RET_t - PCRET_t$	
*100	(1)	(2)	(3)	(4)	(5)	(6)
$PCRET_{t-1}$	**7.408**	**6.896**	**3.047**	**4.652**	**3.260**	**4.098**
	(5.84)	(6.67)	(2.72)	(5.35)	(2.56)	(3.21)
RET_{t-1}		**-4.422**		**-4.183**		**-4.583**
		(-6.88)		(-6.72)		(-7.18)
$INDRET_{t-1}$		**4.783**		-1.341		-0.296
		(3.85)		(-1.27)		(-0.25)
SIZE	-0.052	-0.048	-0.029	-0.023	-0.034	-0.031
	(-1.24)	(-1.12)	(-1.49)	(-1.05)	(-1.56)	(-1.32)
B/M	**0.212**	**0.229**	**0.209**	**0.225**	**0.217**	**0.234**
	(2.35)	(2.50)	(2.93)	(3.02)	(2.91)	(3.02)
MOM	**0.285**	**0.283**	**0.296**	**0.311**	**0.265**	**0.270**
	(2.51)	(2.46)	(2.89)	(3.02)	(2.45)	(2.54)
TURNOVER	**-0.027**	**-0.029**	**-0.025**	**-0.027**	**-0.029**	**-0.031**
	(-3.36)	(-3.51)	(-3.67)	(-3.88)	(-3.92)	(-4.09)
Adj R^2	0.06	0.07	0.03	0.04	0.03	0.04

Table V: Level of Complexity in Complicated Firms, 1977–2009

This table reports Fama-MacBeth forecasting regressions of individual stock returns. The dependent variable is the monthly return of the conglomerate. The explanatory variables are the lagged pseudo-conglomerate return (*PCRET*), and a number of interaction terms with this variable. *Herfindahl* is the Herfindahl Index based on the segment sales of the given firm in a fiscal year, *Market Cap* is the market capitalization of the conglomerate firm at the of June, *Idio Vol* is the idiosyncratic volatility in the prior year, *Res Inst Own* is institutional ownership of the conglomerate firm orthogonalized with regard to firm size at the end of June, *Turnover* is the turnover measured as the average daily turnover in the prior year, and *# of Analysts* is the number of analysts covering the firm at the end of June. All interaction terms are based on indicator variables that take the value of one if the underlying variable is above the sample median in each year and zero otherwise. All regressions also include the dummy itself, lagged *RET*, *INDRET*, *SIZE*, *B/M*, *MOM*, and *TURNOVER* as controls, which are described in Table IV, and are unreported for brevity. Cross sectional regressions are run every calendar month, and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

Dep Variable	Conglomerate Return(t)					
*100	(1)	(2)	(3)	(4)	(5)	(6)
$PCRET_{t-1}$	**8.504**	**5.995**	**8.456**	**7.871**	**7.033**	**6.720**
	(5.77)	(4.60)	(5.09)	(5.38)	(5.24)	(6.23)
$PCRET_{t-1}$*	**-3.458**					
Herfindahl > median	(-3.33)					
$PCRET_{t-1}$*		**3.159**				
Idio Vol > median		(2.43)				
$PCRET_{t-1}$*			**-3.181**			
MktCap > NYSE median			(-2.23)			
$PCRET_{t-1}$*				-1.698		
Res Inst Own > median				(-1.20)		
$PCRET_{t-1}$*					0.361	
Turnover > median					(0.24)	
$PCRET_{t-1}$*						-0.500
#Analyst > median						(-0.37)
CONTROLS	YES	YES	YES	YES	YES	YES
Adj R^2	0.09	0.09	0.09	0.08	0.08	0.08

Table VI: Change of Status and Complicated Processing, 1977–2009

This table reports Fama-MacBeth forecasting regressions of stock returns in two subsamples. We first identify all cases in which a standalone firm transitions into a conglomerate firm. We then include observations within three years prior to the status change in the standalone-status sample, and those within three years subsequent to the status change in the conglomerate-status sample. The dependent variable in columns (1) and (3) is the monthly return of the conglomerate (*RET*), while the dependent variable in columns (2) and (4) is the excess return of the conglomerate over the pseudo-conglomerate (*RET-PCRET*). The explanatory variables are the lagged pseudo-conglomerate return (*PCRET*), the firm's own lagged return (*RET*). All regressions also include *SIZE*, *B/M*, *MOM*, and *TURNOVER*, all of which are measured at the end of June of each year. Cross sectional regressions are run every calendar month, and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

	Standalone Status		Conglomerate Status	
Dep Variable	RET_t	$RET_t - PCRET_t$	RET_t	$RET_t - PCRET_t$
*100	(1)	(2)	(3)	(4)
$PCRET_{t-1}$	**5.198**	0.581	**8.768**	**3.206**
	(3.57)	(1.08)	(5.06)	(2.71)
RET_{t-1}	**-4.903**	**-5.874**	**-2.961**	**-3.342**
	(-4.25)	(-5.01)	(-2.15)	(-2.50)
SIZE	-0.054	-0.033	-0.122	-0.092
	(-0.83)	(-0.61)	(-1.53)	(-1.31)
B/M	0.327	0.225	0.505	0.502
	(1.69)	(1.24)	(1.83)	(1.94)
MOM	0.352	**0.382**	1.612	1.526
	(1.50)	(2.17)	(1.21)	(1.31)
TURNOVER	0.010	0.011	0.019	0.001
	(0.37)	(0.49)	(0.45)	(0.03)
Adj R^2	0.18	0.13	0.17	0.15

Table VII: Analyst Compounding of Information, 1984–2009

This table reports Fama-MacBeth forecasting regressions of changes in analyst earnings forecasts. The dependent variable in columns 1 and 2 is the monthly change in the consensus analyst forecast for the subsequent annual earnings of the conglomerate firm (henceforth *F*), while the dependent variable in column 3 is that of the pseudo-conglomerate (*PCF*). A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The explanatory variables are the lagged *PCF*, the firm's own lagged *F*, and lagged average consensus forecast change of the conglomerate's principal industry (*INDF*). All regressions also include *SIZE*, *B/M*, *MOM*, and *TURNOVER*, all of which are measured at the end of June of each year. Cross sectional regressions are run every calendar month and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

Dep Variable	F_t	F_t	PCF_t
*100	(1)	(2)	(3)
PCF_{t-1}	**6.389**	**5.370**	
	(2.76)	(2.51)	
F_{t-1}		**37.014**	0.682
		(19.84)	(0.31)
$INDF_{t-1}$	**38.558**	**9.651**	**32.788**
	(8.53)	(2.57)	(17.25)
SIZE	**0.033**	**0.022**	**0.010**
	(8.25)	(8.25)	(7.29)
B/M	**-0.047**	**-0.040**	**-0.010**
	(-3.16)	(-3.71)	(-2.10)
MOM	**0.100**	**0.056**	0.005
	(5.31)	(4.37)	(0.84)
TURNOVER	**-0.002**	**-0.001**	**0.000**
	(-2.34)	(-2.06)	(-2.11)
Adj R^2	0.12	0.19	0.21

Table VIII: Industry Sentiment, cross sectional regressions 1983–2000

This table reports Fama-MacBeth forecasting regressions of stock returns. The dependent variable in column 1 is the monthly return of the paired pseudo-conglomerate (*PCRET*), in column 2 is the monthly return of the conglomerate (*RET*), and in column 3 the excess return of the conglomerate over its paired pseudo-conglomerate (*RET-PCRET*). A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. In Panel A, the explanatory variables include the lagged pseudo-conglomerate small-trade imbalance in the previous year (*PCIMBL*) and the firm's own small trade imbalance in the previous year (*IMBL*). In Panel B, the explanatory variables include the pseudo-conglomerate small-trade imbalance (*PCIMBL*) and the firm's own small trade imbalance in the contemporaneous month (*IMBL*). Other control variables include the firm's own lagged return (*RET*), and lagged return of the corresponding industry portfolio to the conglomerate's principal industry (*INDRET*). All regressions also include *SIZE*, *B/M*, *MOM*, and *TURNOVER*, all of which are measured at the end of June of each year. Cross sectional regressions are run every calendar month and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

Panel A: Industry Sentiment on Future Returns			
Dep Variable	$PCRET_t$	RET_t	RET_t - $PCRET_t$
*100	(1)	(2)	(3)
$PCIMBL_{t-1}$	-0.090	0.023	**0.113**
	(-1.81)	(0.45)	(2.08)
$IMBL_{t-1}$		**-0.036**	**-0.037**
		(-2.11)	(-2.23)
RET_{t-1}	0.160	**-4.320**	**-4.479**
	(0.88)	(-6.01)	(-6.16)
$INDRET_{t-1}$	**6.206**	**9.529**	**3.323**
	(4.68)	(6.26)	(2.63)
SIZE	0.011	0.044	0.033
	(0.25)	(0.68)	(0.86)
B/M	-0.003	**0.373**	**0.376**
	(-0.03)	(2.99)	(3.51)
MOM	0.062	**0.437**	**0.375**
	(1.10)	(2.80)	(2.64)
TURNOVER	-0.046	**-0.295**	**-0.248**
	(-1.12)	(-2.35)	(-2.38)
Adj R^2	0.11	0.07	0.05

Table VIII: Industry Sentiment, cross sectional regressions (continued)

Panel B: Industry Sentiment on Contemporaneous Returns			
Dep Variable	$PCRET_t$	RET_t	RET_t - $PCRET_t$
*100	(1)	(2)	(3)
$PCIMBL_t$	**1.233**	-0.419	**-1.652**
	(2.53)	(-1.11)	(-2.38)
$IMBL_t$		**3.017**	**3.004**
		(4.34)	(4.03)
RET_{t-1}	0.456	**-4.070**	**-4.526**
	(0.70)	(-5.02)	(-5.35)
$INDRET_{t-1}$	**9.384**	**10.495**	1.111
	(4.84)	(7.26)	(0.59)
SIZE	-0.027	0.061	0.088
	(-0.63)	(1.01)	(1.28)
B/M	0.112	**0.636**	**0.524**
	(1.20)	(4.04)	(3.41)
MOM	-0.058	**0.319**	**0.377**
	(-1.03)	(2.37)	(2.74)
TURNOVER	-0.002	**-0.598**	**-0.595**
	(-0.07)	(-3.43)	(-3.62)
Adj R^2	0.15	0.09	0.07

Table IX: Robustness Tests, 1977–2009

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month, all conglomerate stocks are ranked in ascending order on the basis of the return of a portfolio of their pseudo-conglomerate at the end of the previous month. A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The ranked stocks are assigned to one of 10 decile portfolios. All stocks are value (equally) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights. This table includes all available stocks with stock price greater than $5 at portfolio formation. L/S is the alpha of a zero-cost portfolio of conglomerate firms that holds the firms with the top 10% pseudo-conglomerate returns and sells short the firms with the bottom 10% pseudo-conglomerate returns in the previous month. In columns (1) and (2), a pseudo-conglomerate is constructed based on the conglomerate's sales in each industry segment, while in columns (3) and (4) a pseudo-conglomerate is constructed based on the conglomerate's assets in each industry segment. Larger (smaller) cap stocks are those with market capitalization above (below) the median of the NYSE sample. Higher (lower) idio vol stocks are those with idiosyncratic volatility above (below) the median of the current sample in the prior year. DGTW characteristic-adjusted returns are defined as raw monthly returns minus the returns on a value weighted portfolio of all CRSP firms in the same size, book-to-market, and one year momentum quintile. Returns are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold.

Conglomerate Return (L/S)					
	# months	Segment Sales		Segment Assets	
Weight		EW	VW	EW	VW
		(1)	(2)	(3)	(4)
All firms (5-factor alpha)	387	**1.01%**	**0.87%**	**1.00%**	**0.66%**
		(4.26)	(2.56)	(4.59)	(2.13)
All firms (DGTW adjusted)	387	**0.84%**	**0.72%**	**0.77%**	**0.66%**
		(5.34)	(3.34)	(4.46)	(2.90)
Smaller firms (5-factor alpha)	387	**1.22%**	**1.16%**	**1.29%**	**1.17%**
		(5.13)	(4.96)	(4.94)	(4.26)
Larger firms (5-factor alpha)	387	**0.75%**	**0.66%**	**0.78%**	0.64%
		(2.80)	(2.01)	(2.92)	(1.91)
Lower idio-vol (5-factor alpha)	387	**0.68%**	0.44%	**0.61%**	0.54%
		(3.48)	(1.37)	(2.31)	(1.64)
Higher idio-vol (5-factor alpha)	387	**1.20%**	**1.27%**	**1.13%**	**0.80%**
		(4.27)	(3.16)	(4.22)	(2.05)

Table X: Cross sectional regressions, weekly returns, 1977–2009

This table reports Fama-MacBeth forecasting regressions of stock returns. The dependent variable is the *weekly* return of the conglomerate (*RET*). The explanatory variables include past *month* (i.e., four-week cumulative) pseudo-conglomerate returns (*PCRET*) lagged over the four weeks prior to the weekly RET being considered. A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. All regressions also include the firm's own lagged return (*RET*), and lagged return of the corresponding industry portfolio to the conglomerate's principal industry (*INDRET*), defined similarly as in Table IV. Other controls include *SIZE*, *B/M*, *MOM*, and *TURNOVER*, all of which are measured at the end of June of each year. Cross sectional regressions are run every calendar week and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 52 lags). Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

Dep Variable	RET_t	RET_t	RET_t	RET_t
*100	(1)	(2)	(3)	(4)
$PCRET_{t-1}$	**2.558**			
	(7.29)			
$PCRET_{t-2}$		**1.860**		
		(6.65)		
$PCRET_{t-3}$			**1.260**	
			(5.03)	
$PCRET_{t-4}$				**1.019**
				(4.53)
CONTROLS	YES	YES	YES	YES
Adj R^2	0.06	0.05	0.05	0.05

Figure 1: Size distributions, 1977–2009

This figure shows the size distributions of standalone firms and conglomerate firms. At the end of each year, all firms are classified into ten size deciles based on NYSE market capitalization breakpoints. P1 is the lowest NYSE market capitalization decile, while P10 is the highest.

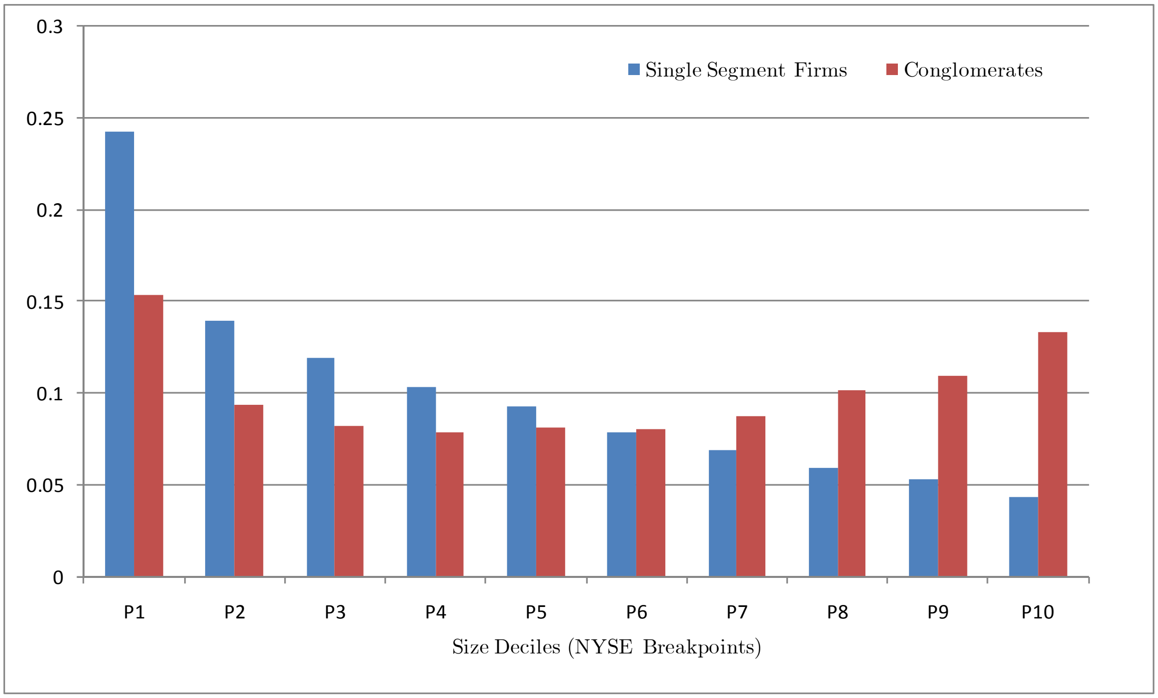

Figure 2: Cumulative Returns to the Hedge Portfolio

This figure shows the cumulative return to the hedge portfolio in the six months after portfolio formation. At the beginning of every calendar month, all conglomerate stocks are ranked in ascending order on the basis of the return of a portfolio of their pseudo-conglomerate at the end of the previous month. A pseudo-conglomerate is simply a portfolio of the conglomerate firm's industry segments constructed using solely the stand alone firms from any given industry. The ranked stocks are assigned to one of 10 decile portfolios. All stocks are value (equally) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights. L/S is the alpha of a zero-cost portfolio of conglomerate firms that holds the firms with the top 10% pseudo-conglomerate returns and sells short the firms with the bottom 10% pseudo-conglomerate returns in the previous month. The graph shows returns to both equal-weighted (blue) and value-weighted (red) portfolios.