Vertical Integration and Predictable Returns

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First Draft: June 4, 2010

This Draft: February 15, 2011

*We thank Rüdiger Fahlenbrach and Norman Schürhoff, Julien Cujean, Amit Goyal, Anita Kulak, Matthias Kurmann, Olivier Ledoit, Pascal St-Amour and René Stulz for helpful comments and suggestions. Correspondence: Kulak: Swiss Finance Institute at EPFL, Quartier UNIL-Dorigny, Extranef 129, CH-1015 Lausanne, Switzerland; e-mail jan.kulak@epfl.ch; Tel: +41 21 693 0129. Schmidt: Swiss Finance Institute and Faculty of Business and Economics, University of Lausanne, Extranef 130, CH-1015 Lausanne, Switzerland; e-mail cornelius.schmidt@unil.ch; Tel: +41 21 692 3677. Schmidt gratefully acknowledges financial support from the Swiss National Science Foundation.

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Abstract

We propose a novel setting to test how the presence of attention constraints affects stock prices. Our setting exploits the particular industry exposure of *vertically integrated firms*. Because of inter-segment sales of goods, the relative size of individual segments within such firms, in an accounting sense, is a misleading indicator for the firm's overall exposure to industry shocks. We hypothesize that attention constrained investors will tend to neglect this detail, leading to systematic pricing mistakes after confounding, industry-specific news shocks. In line with this hypothesis, we find evidence of predictable price corrections in post-news periods - in particular in the time around firms earnings announcements. A fully implementable long-short equity strategy based on the phenomenon leads to significant risk-adjusted excess returns. Security analysts' earnings forecasts exhibit a predictable error in the same direction as stock prices.

1 Introduction

A growing number of empirical studies show evidence of delayed stock price reactions to public news. Contrary to the prediction of the *efficient market hypothesis*, stock prices systematically seem to underreact initially to a variety of types of news and only gradually adjust in post event periods.[1] The common interpretation of these findings is that investors are inattentive to the public information that is being analyzed. In theoretical models, this *investor inattention* is rationalized by the idea that investors are bounded in the time or in processing capabilites that they can devote to the collection of information. Even when information is public, and hence free in monetary terms, investors therefore do not collect all relevant information.[2]

[1]Examples of the news events that have been examined in this direction include exchange rate changes (Bartov and Bodnar, 1994), news regarding related firms (Ramnath, 2002; Hou, 2007; Cohen and Frazzini, 2008), news regarding related industries (Hong, Torous, and Valkanov, 2007; Menzly and Ozbas, 2010), news regarding related countries Rizova (2010),information in accounting statements (Sloan, 1996; Hirshleifer, Hou, Teoh, and Zhang, 2004), information about demographic changes in the consumer population (DellaVigna and Pollet, 2007), information in soccer-bets odds (Palomino, Renneboog, and Zhang, 2009), and news stories in the non-financial press (Huberman and Regev, 2001).

[2]Theoretical models of the consequences of inattention on stock prices include Peng and Xiong (2006), DellaVigna and Pollet (2007), Hong, Torous, and Valkanov (2007), Menzly and Ozbas (2010)

Although the above view of investor inattention appears attractive from a modelling perspective and appropriate for a variety of empirical settings, it is also very restrictive. We argue that attention constraints should not only affect the information that investors *collect*, but also - and probably to a much larger extent - how this information is used. Clearly, the collection of individual pieces of information is often much less time consuming than the analysis required to correctly use this information. If investors are constrained, it therefore seems plausible that investors not only cut short on the attention spent on information collection, but also on the attention spent analyzing and interpreting this news. We expect investors to use rules of thumb, to make back-of-the-envelope approximations, or to perform superficial analysis to cope with attention constraints.

In this article we test the hypothesis that stocks are at times inefficiently priced due to the superficial analysis of investors. To do so, we choose an empirical setting in which it seems plausible that a large number of investors are misled by the same approximations. Moreover, our setting allows us to distinguish the effect of *investor superficiality* from that of investor inattention to news. Specifically, our setting focuses on the stock price reaction of vertically integrated firms to confounding industry news events. Vertically integrated firms are firms with multiple operating segments along the supply chain. Examples would be a producer of cosmetics products that owns some of its chemical suppliers, or a producer of soft-drinks that operates fast-food chains to retail its product. We investigate whether the stock prices of these firms contain a systematic error after industry news that affect the individual segments's industry sectors differently.

To best explain why this represents a test of our hypothesis of investor superficiality, consider a stylized example. Take the beverages-fast-food producer from above and imagine some news that imply a reduction in future fast-food sales. How will investors impound this news into their valuation of the firm? For attention-constrained investors, we hypothesize that a popular way to answer this question will be to estimate the impact of the news on the future profitability of the beverages and the fast-food industries separately, perhaps based on the recollection of similar past events or based on intuitive judgement, and then to use the relative size of the individual segments, to form a weighted average the impact of the news on the integrated firm.

The key idea of our empirical setting is that this weighting approach will lead investors to systematically misjudge the impact of the news for the vertically integrated firm. The reason, as we verify empirically below, is that vertically integrated firms are on average more exposed to shocks affecting their "downstream" industry than suggested by the relative size of its downstream segment, and less to shocks affecting their "upstream" industry. The likely reason for this shifted exposure is that the upstream segment in a vertically integrated firm inherits much of the downstream segment's industry exposure through its intimate supplier relationship with its downstream segment. The beverage producer, for example, will not only witness reduced profits from his fast-food segment, but also record reduced beverage profits. If investors disregard this indirect exposure in their analysis, they will tend to underweight the relevance of downstream industry news and overweight the relevance of upstream industry news.[3] Section 2 reviews this argument more carefully.

Our empirical analysis tests for valuation errors resulting from this mistake.[4] The empirical hypothesis is that vertically integrated firms will be *overvalued* after downstream news that is bad relative to upstream news (as in the example above), and *undervalued* after downstream news that is good relative to upstream news. To implement this test, we follow Hong, Torous, and Valkanov (2007) and Menzly and Ozbas (2010), and use the stock returns of industry peers to measure industry news. That is, for each vertically integrated firm in our sample, we track the stock returns of all single-segment industry peers, and use them to compute the returns on two "news" portfolios: one representing the upstream industries and one representing the downstream industries.[5] We then test for systematic valuation errors on the stock of the vertically integrated firm by investigating whether large deviations between the news portfolios predict subsequent returns of the vertically integrated firm. The idea is that any misvaluation should lead to predictable price revisions on the stock once the malinformed investor group learns about their initial judgement mistake (See, for example, Baker, Ruback, and Wurgler (2007) for a similar argument).

[3] Our identification strategy is similar to those of Cohen and Frazzini (2008) and Menzly and Ozbas (2010), who argue that investors fail to pay attention to firm and industry news that are linked to their investments through customer-supplier relationships. The crucial difference in our setting is that we focus on supplier links *within* one firm. This distinction is important with regards to the economic interpretation of our findings as we discuss below.

[4] With limits to arbitrage (e.g., Shleifer and Vishny (1997), Wurgler and Zhuravskaya (2002)), it is not necessary for *all* investors to fall trap to the hypothesized inference mistake in order for stock prices to be biased. See, for instance, Barberis and Thaler (2003) or Hong and Stein (2007) for discussions.

[5] Our methodology to identify vertically integrated firms builds on the approach of Fan and Lang (2000) and uses data from the US Bureau of Economic Analysis (BEA) that details the historical exchange of goods between industry pairs in the US. We delay the details to Section 3.

Our results indeed support the hypothesis that market participants misjudge the implications of conflicting industry news. The differential between lagged downstream and upstream news over a firm's fiscal quarter is strongly predictive for the firm's returns during the subsequent month, in which the firm announces its quarterly results. The direction of the predictability pattern is exactly in line with initial misjudgements described above. Moreover, corroborating the idea that the predictability stems from an ex-post correction of earlier pricing mistakes, most of the return predictability arises in a few days around the day when the vertically integrated firm announces quarterly earnings.

To provide a sense of the magnitude of the effect, consider the average announcement month returns on vertically integrated firms with extreme deviations in upstream and downstream news portfolios over the previous fiscal quarter quarter. When we sort vertically integrated firms into quintiles according to the news differential, we find a positive mean abnormal return of 1.67 percent in the quintile representing lagged downstream outperformance, over a fifteen-day window around the firm's quarterly earnings announcement. In contrast, firm-quarters that were preceeded by a relative underperformance of downstream peers have a mean abnormal return return of only 0.43 percent. The difference of 1.24% is statistically significant (t-stat = 2.5) and robust to clustering at both firm and year level.

We next investigate whether the effect gives rise to a trading strategy. We construct a simple sorting procedure that assigns firms into predicted winner and looser portfolios according to both, their estimated degree of vertical integration and the degree by which their downstream peers outperformed upstream peers. We trade only on vertically integrated firms, and only during their month of quarterly earnings announcements. The resulting monthly long-short strategy that buys predicted winners and sells predicted loosers leads to a significant four-factor alpha of 87 basis points per month equal-weighted and 1.79% value-weighted (t-stats 2.15 and 3.29, respectively).

Since, taken as a whole, the above results support the notion that market participants make mistakes in judging the relevance of industry shocks for vertically integrated firms, we also test whether a similar bias exists in the earnings-per-share (EPS) forecasts of security analysts. To this aim, we compute median consensus forecasts that coincide with the timing of the news portfolios we used in earlier steps and test whether these forecasts include the same systematic bias that we found in stock prices. The resulting forecasts show a pattern similar to stock returns: After downstream outperformance the mean earnings surprise (over the consensus forecast) is significantly larger than after downstream underperformance quarters.[6]

Our findings contribute to an extant literature that investigates whether conglomerates pose a more complex valuation task than stand alone firms. Gilson, Healy, Noe, and Palepu (2001), for example, show evidence in support of this notion based on the precision of analyst forecasts before and after segment spin-offs by conglomerate firms. In contemporaneous paper to ours, Cohen and Lou (2010) argue that conglomerates pose a more complex information processing task show evidence of a lead-lag effect from single-segment to multi-segment firms in line with this idea. We differ from these articles in that we identify a very specific mechanism that makes multi-segment firms difficult to understand - namely intra-firm links among segments - that has not previously been studied to our knowledge.

Our paper is also related to a growing literature that documents return cross-predictability between economically linked firms and industry sectors. Foremost, Menzly and Ozbas (2006), Cohen and Frazzini (2008), Hong, Torous, and Valkanov (2007), Menzly and Ozbas (2010) find that supplier-customer relationships between firms and industries induce return lead-lag effects across pairs of these.[7] We complement these findings by showing that customer-supplier links can even lead to return predictability if such links exist *within* a single firm. This represents an interesting extension of the existing literature because of the implications for the underlying economic channel.

The standing explanation for previous findings is based on the informational segmentation of investors that specialize in individual stocks or industries. These investors are thought to collect information only inside their area of expertise and learn about related-firm or industry information only with a lag. Since our findings are based on economic links *within* a single firm, they cannot easily be explained by an investor segmentation channel.[8] Instead, our

[6]The evidence in EPS forecasts is not robust to non-parametric tests for differences in medians or ranks of forecast errors. The effect in mean forecaste errors thus appears driven by extreme values. We believe the results to be of interest nevertheless to the extent that extreme forecast errors are likely to be also associated with most extreme stock price reactions.

[7]See also Rizova (2010) for evidence suggesting that similar patterns exist between pairs of countries.

[8]An explanation based of segmentation would predict a lagged response of the conglomerate's stock to related customer and supplier firms and industries. In particular, if one assumes that investors in conglomerates are specialized on the firm's core industry, then this argument would - among other things - predict that the conglomerate outperform (underperform) after the industries of the firm's small secondary segments outperformed (underperformed). This prediction is the same as the empirical prediction we make based on a misunderstanding of industry exposure for backward integrated firms, and we thus cannot distinguish among the two explanations from backward integrated firms. However, the predictions differ for forward integrated

finding suggests that pricing errors are induced by a lack of understanding of the economic links itself, rather than by the salience of related industry information.

The remainder of the paper is structured as follows. Section 2 briefly revisits the industry exposure of vertically integrated firms. Section 3 describes the data, explains how we identify vertically integrated firms, and how we compute upstream and downstream news portfolios. Section 4 presents the main results. Section 5 examines EPS forecast errors and Section 6 concludes.

2 Industry Exposure of Vertically Integrated Firms

Our empirical setting relies on the idea that vertically integrated firms feature a pronounced industry exposure to downstream industry shocks. We will verify this conjecture empirically in Section 4.1, using the accounting profits of vertically integrated firms and their industry peers. Here, we want to briefly discuss why we expect this to be the case.

To guide the discussion, Figure 1 shows a stylized graphical representation of a set of firms. Panel A depicts a pair of firms that operate respectively in two industries A and B. For the sake of our discussion, these firms should be seen as representatives of typical firms in the industries A and B. Firm A sells a fraction $\bar{\theta}$ of its output to firm B and a fraction $(1-\bar{\theta})$ of its output to a third outside industry C. The output of industry A is thus an intermediate good that is used in the production of industries B and C. Industry C represents a composition of third industries, other than A and B. Since firms A and B are representative firms of industries A and B, fractions $\bar{\theta}$ and $(1-\bar{\theta})$ can equally well be interpreted as coefficients measuring the transfer of goods between the *industries* A and B.

Figure 1 about here

Panel B of the figure shows a vertically integrated firm with two segments. The two segments respectively also operate in industries A and B, just like the two representative firms on the left. Similar to the stand-alone firms, the upstream segment A supplies a fraction of its output to the firm's downstream Segment B, which in turn uses this output in the production of its own output good. The segment's sales fraction is now denoted by θ.

firms.

The remainder of Segment A's output $(1-\theta)$ is sold to the same universal outside market, denoted by C.

It is immediate to see that both the representative stand-alone firm of industry A (left) and the segment operating in industry A (right) feature an exposure to aggregate shocks affecting industries B and C. An aggregate demand shock affecting firms in industry B, for example, would transmit to firms in industry A because it would affect the demand for the intermediary input good that B-type firms need demand for their production. The same is true for any other shock affecting the operations of firms in industry B that would affect the firms' demand for input goods from industry A (e.g. supply shocks to another input good, changes to competition, productivity shocks, etc.).

The magnitude of the exposure to such downstream shocks will generally depend on the magnitude of the output coefficients θ and $\bar{\theta}$. An A-type firm that sells 90 percent of its output to firms in industry B ($\bar{\theta} = 90\%$) will ceteris paribus be more exposed to various shocks to industry B than an A-type firm that only sells 10 percent of its output to firms in industry B ($\bar{\theta} = 10\%$). By the same token, the former firm will be less exposed to shocks to industry C than will be the latter.

Our reason to suspect that vertically integrated firms feature a disproportionally high exposure to downstream shocks is simply that vertically integrated firms have θ coefficients of larger magnitude than their stand-alone peers. As a consequence, the value of a conglomerate's upstream segment will depend more on industry B than the value of other firms in industry A and less on other customer industries C.

3 Data

We use data from the CRSP-Compustat merged (CCM) database, the Compustat annual and segment files and I/B/E/S from 1984 to 2007. Since our analysis focuses on vertically integrated firms, we require detailed data about firms operations by business segments. In the US, firms are required to report such disaggregate data in their annual and interim financial statements since the release of SFAS No. 14 in 1976.[9] For Compustat firms, this segment

[9] In particular, firms are required to disclose individual financial information for any industry segment comprising more than 10% of consolidated yearly sales, assets, or profits. Regulation SFAS No. 14 was issued in December of 1976. The regulation was replaced by SFAS No. 131 on December 15, 1997, which governs the disclosure of segment information today. The regulations impose identical size cutoffs for firms' segment reporting requirements, but differ in the degree to which firms have discretion in defining operating segments

information is collected in the Compustat Segments database, and includes segment-level sales and assets, and segments' Standard Industry Classification (SIC) code as assigned by Compustat.[10] We extract this segment data and use it to identify the industry composition of all firms listed on the CRSP-Compustat merged database during the 1984-2007 time period. We consider any firm to be a single-segment firm if it has either one single segment listed in the Segments tapes or no entry at all. All firms with multiple segments entries are considered multi-segment, and potentially vertically integrated.

We then apply a set of selection criteria to this intitial sample to ensure that our segment data accurately represent the industry composition of multi-segment firms. A detailed description of this selection procedure is provided in the Appendix. To list the most notable aspects here, we eliminate segment entries that represent overhead expenses or intersegment-eliminations, and require firms to have non-missing SIC codes and non-negative sales for all remaining segments listed in the Compustat Segment tapes. Following Berger and Ofek (1995), we discard firms with large discrepancies between segment-level and firm-level data in the Compustat Segments tapes and Annual tapes respectively, and firms with segments in the financial services industry (SIC codes between 6000 and 6999). Finally, to make sure that multi-segment firms that enter our final sample have a liquid trading market for their stock and have an active following by market participants, we require firms to have stock market capitalization in excess of $20 million, a stock price above a threshold of $1, and be followed by at least one security analyst in a given quarter as judged by the quarterly consensus forecast records on the I/B/E/S tapes.

3.1 A Measure of Vertical Integration

As a central step to our study, we have to determine which of the multi-segment firms in our sample are vertically integrated. Several previous studies have performed a carefull in-depth analysis of a small sample of firms to determine intersegment links within these firms. Although this approach probably has the advantage of yielding very accurate classifications of firms, the approach is clearly impractical given the size of our sample and the data we have

for reporting purposes. The older Regulation SFAS No. 14 required firms to classify items to segments based on industry classification, whereas the new standard requires disaggregated information to be presented based on how management internally evaluates the operating performance of its business units. Berger and Hann (2003) provide a more detailed discussion of the differences and evaluate the impact of the regulation change on reporting practice.

[10]The data are available back to 1979 and up to 2007 in the current vintage of Compustat.

at hand. We therefore instead build on Fan and Lang (2000) and use macro data provided by the US Bureau of Economic Analysis (BEA) to classify firms in our sample into likely candidates of being vertically integrated.

In particular, we use the *Use Tables* of the Input-Output Benchmark accounts that are published every five years by the BEA. Among other statistics, these tables provide a statistic called *direct requirements coefficient*, which we denote v_{ij} following BEA notation. For the aggregate US economy, this coefficient details the flow of goods from one industry sector i to a second industry sector j over the five year period that BEA covers. Specifically, v_{ij} represents the dollar value of industry output i that was purchased by industry j to produce one dollar of industry j output.

We use this coefficient as a simple means of judging whether, amoung pairs of segments within a conglomerate, one is likely to be a customer of the other. To each pair of segments in our dataset, we match the two corresponding direct requirements coeffients (one for each direction of exchange) by the segment's 4-digit SIC code.[11] As of now, we set missing v_{ij} coefficients to zero for the years 1977 and 1982 if the SICs for i and j industries both exist in the BEA correspondance tables. If we cannot identify all links between the secondary and the primary segment we drop the firm from our sample. Specifically, we use the data of the Benchmark Accounts of 1977, 1982, 1987, 1992, 1997, and 2002. Since the BEA publishes its accounts with a five-year time lag, and we want to make sure that we only use information that is publically available, we match data from the individual accounts to our data with the same five-year lag.

We then analyse the set of intersegment coefficients to classify firms into being either forward integrated or backward integrated firms.[12] To keep this classification procedure transparent and intuitive, we only consider the exchange of goods between a single segment that we can clearly identify as the core or primary segment of the firm and all other, sec-

[11]The BEA classifies industries according to its own industry classification code (IO-Code), but provides concordance tables between this industry code and SIC codes prior to 1997 and NAIC codes thereafter. We use these concordance tables, in combination with SIC-NAIC concordance tables from the CENSUS website, to translate all industries into SIC codes. If a SIC corresponds to multiple IO-Codes (because of an overlap of industry definitions), we form the average of IO-Code based v_{ij} coefficients to arrive at SIC code based coefficients. The SIC-IO matching works poorly for the Benchmark Accounts of 1977 and 1982. This may be due to the fact that the Input-Output matrix is unbalanced in these years. We do not know whether zero requirements coefficients are systematically omitted. We are currently writing with the BEA staff to figure this out.

[12]Recall that a forward integrated firm has a single core upstream (i.e., supplier) segment and one or several smaller downstream (i.e., customer) segments. A backward integrated firm has the reverse.

ondary, segments. A firm's primary segment is first identified by checking which of a firms' segments has a SIC code that matches the firm's overall SIC code. To avoid false classifications, we additionally require that the identified segment accounts for at least 70%[13] of total firm sales.

Given a single primary segment of each multi-segment firm, we then compute a score, $VERT$:

$$VERT = \sum_{i \in S} \left(\frac{w_i}{w_S} (v_{iP} - v_{Pi}) \right) (1)$$

where w_i denotes the sales weight of segment i within the conglomerate and where P and S respectively denote primary and secondary. The term w_S thus denotes the aggregate weight of all secondary segments and v_{iP} represents the dollar amount of goods of industry i used by the primary industry P - based on the BEA accounts.

The score $VERT$ thus averages, across all secondary segments, the net flow of goods between the industry sectors of primary and secondary segments respectively. Intuitively, the measure thus tells us whether the firm's small segments, as a group, are likely to be in a customer or a supplier relationship with the firm's core segment, based on the segments' industry classification and the inter-industry flow of goods in the US. A large positive value of $VERT$ signifies that the primary segment probably purchased more from the group of secondary segments than it sold to them. An extreme negative value, in contrast, signifies that the primary segment is likely in a customer relationship with its secondary segments.

We therefore consider firms with large positive values of $VERT$ as being backward integrated, and firms with extreme negative values as forward integrated. In particular, for the purpose of cross-sectional tests below, we consider two subsets of firms with extreme values of $VERT$ as judged by the cross-sectional distribution. We assign firms to a *backward* integrated group if their $VERT$-score is positive and exceeds the median score of all positive-score firms. Similarly, we assign firms to a *forward* integrated set if their score is negative and below the median score of all negative-score firms.

Table 1 here

Table 1 shows summary statistics for firms with a non-missing and non-zero value of $VERT$. These are the firms that enter all analyses to follow. Panels B and C of the table,

[13]Our results remain qualitatively unchanged if we change this threshold to 65% or 75%.

moreover show summary statistics for the two forward integrated and backward integrated subsets described above. As can be seen our analysis focuses on very large firms. The median market capitalization of the firms in our sample exceeds $700 million. The same is true for both forward and backward integrated subsets. Our assignment mechanism has assigned 2,651 firm-quarter observations to a backward integrated sample, and 2,214 to a forward integrated sample. Importantly, the two subsamples differ very little with respect to all listed variables except for their vertical integration score, which differs by construction.

3.2 Upstream and Downstream Industry Portfolios

For all firms with non-zero values of the vertical integration score $VERT$, we next compute the returns on two portfolios. One portfolio represents the upstream industries of the vertically integrated firm, the other the downstream industries. Both portfolios are strictly composed of single-segment firms to ensure that they represent industry dynamics as cleanly as possible.

We begin by assigning each stand-alone firm to an industry according to its four-digit SIC code. Based on this industry assignment, we calculate equal-weighted returns over overlapping three-month intervals. At the end of a month m, we thus record the three-month return since $m-3$. At the end of the next month $m+1$, we record the three-month industry return since $m-2$, and so forth. For an industry return to exist, we require that the return be computed based on at least five single-segment firms. If we do not find at least five single-segmented firms, we enlarge the industry definition by deleting the last digit of the SIC. We impose this requirement to ensure that industry portfolios do not contain excessive levels of ideosyncratic firm volatility.

After calculation of industry portfolio returns, we form the two separate portfolios that represent the upstream and downstream industries respectively for each multi-segment firm in our sample. These portfolios are simply computed as sales-weighted averages of the industry portfolios that represent the firm's upstream or downstream industries. If a firm has a single upstream segment, for instance, then the firm's upstream portfolio is simply the single industry portfolio has the same SIC code as the firm's upstream segment. If a firm has multiple upstream segments, then the firm's upstream portfolio is the average of all matching industry portfolios, weighted by the size of the firm's upstream segments in terms of sales. To classify segments into upstream or downstream segments we simply rely on the score measure $VERT$ computed above. If a firm has a positive score (and secondary segments are thus likely to be downstream segments), we treat all secondary segments as downstream and the primary segment as upstream, and vice versa.

In terms of timing, we only record one single upstream and and one single downstream return for each firm-quarter in our multi-segment sample. The return is chosen such that it covers the three-month period representing the firm's fiscal quarter. This choice is made to ensure that the upstream and downstream portfolio returns represent industry news that are revealed over the firm's fiscal quarter period. Since we test for price corrections at the time of quarterly earnings releases, this choice seems the most natural in the sense that investors should primarily learn from these releases about misjudgements made during the quarter.

Since a misunderstanding industry exposure will only lead to mispricings when industry news diverge, we generally do not use the two industry portfolios in isolation but instead compute the divergence between the two. Formally, for each firm-quarter we compute

$$DSOP_{i,t} = [R_{i,t}^{downstream} - R_{i,t}^{upstream}] * w_i^S \tag{2}$$

where, as before, w_i^S is the cumulative weight of all secondary segments of the firm.

DSOP (Down-Stream Out-Performance) thus represents the quarter specific divergence between downstream and upstream industry returns for a given firm i. The measure is weighted by the size of secondary segments (i.e., the smaller of downstream segments or upstream segments) to account for the fact that the pricing error we test for should be more severe, the larger the small segments of the firm. Intuitively, if small segments only represent a minimal fraction of the firm - be they upstream or downstream - any pricing error due to a misunderstanding of the resulting, factual industry exposure must be very small. For the purpose of our tests of market efficiency, DSOP thus has the desired properties of (a) measuring the relative performance of upstream and downstream industries, based on other single-segment peers, and (b) reflecting the economic importance of any divergence between upstream and downstream industries given the particular composition of a vertically integrated firm i.

4 Empirical Results

4.1 Industry Exposure

We begin by presenting preliminary evidence on the central assumption underlying our empirical design, that the industry exposure of vertically integrated firms is shifted towards downstream industries. To do so, we construct firm-level and upstream- and downstream-industry-level measures of profitability for each vertically integrated firm in our sample (i.e., each member of the backward or forward subset of our sample). We then estimate regressions in the pooled cross-section of our dataset of the form

$$\Delta ROA_{i,t} = \alpha_i + \theta^{DOWN} \Delta ROA_{i,t}^{DOWN} + \theta^{WEIGHTED} \Delta ROA_{i,t}^{WEIGHTED} + \epsilon_{i,t} \tag{3}$$

where $\Delta ROA_{i,t}$ is the quarter-on-quarter change in return on assets of firm i in fiscal quarter t. $\Delta ROA_{i,t}^{DOWN}$ represents the average contemporaneous change in ROAs of all matched stand-alone firms in the downstream industries of the vertically integrated firm i. $\Delta ROA_{i,t}^{WEIGHTED}$ represents a weighted basket of all industry sectors in which firm i operates, by weighting industry ROA changes by firm i's sales in these industries.

We measure firm-level ROA as the ratio of cash-flow to total assets, where cash-flow is the sum of net income and depreciation and amortization. Downstream and weighted profitability measures are computed from the set of stand-alone firms in our sample in a similar fashion as the returns for upstream and downstream portfolios. First, a $\Delta ROA_{i,t}$ is computed for each stand-alone firm separately; then industry-wide measures are computed as the industry average of $\Delta ROA_{i,t}$s. Finally, if firm i has multiple upstream or downstream segments, industry profitability measures are weighted by the firm's segment sales.[14] Depending on the specification, α_i represents either a constant term or a firm fixed effect. In addition to the above variables, we also add a control for market-wide changes in ROA, $\Delta ROA_{i,t}^{Market}$ in some of our specifications, which is computed as the average ROA change of all available stand-alone firms in our sample. Standard errors are clustered by firm and year.

[14] A complication arises in computing industry averages due to non-overlapping fiscal quarters of industry members. That is, because firms have fiscal quarters ending in different months, we have to make a choice which firms to allow entering the upstream and downstream industry averages. As a simple means to preserve a large size of industry portfolios, we consider all firms whose fiscal quarters overlap with the fiscal quarter of the vertically integrated firm i.

The results in table 3 support our underlying assumption regarding the industry exposure of vertically integrated firms. Column 1 presents results of a reduced regression including no $\Delta ROA_{i,t}^{DOWN}$ term. As expected, a vertically integrated firm's quarterly change in ROA is positively correlated with the contemporaneous ROA changes in firms that operate in the same industry sectors as the vertically integrated firm. The coefficient estimate suggests that a unit change in the representative industry protfolio's ROA is on average associated with a 27% change on the vertically integrated firm. The explanatory power of industry peers is stronger than that of market-wide ROA changes, whose coefficient estimate is positive but insignificant.

Table 3 here

Column 2 adds to the regression a separate term representing only ROA changes the firm's downstream industries. Intuitively, the addition of this separate term allows downstream industries to obtain a larger coefficient loading than is restricted by the the sales weighting in $\Delta ROA_{i,t}^{WEIGHTED}$. In line with our hypothesis, downstream industries on average require a larger coefficient. The correlation with downstream industry peers fundamentals is thus larger than implied by a simple sales weighting of the firm's segments. Columns 3 and 4, repeat slight variations of this regression to show that the finding is robust to adding firm-fixed effects, or dropping the market wide ΔROA term. In all specifications, the partial correlation with downstream industry profitability is statistically significantly larger than implied by a firm's segment sales.

4.2 Downstream-Upstream Return Predictability Effects

We now test whether the stock returns of vertically integrated firms are predictable based on the lagged return differential between upstream and downstream portfolios. To do so, we sort firms into quantiles based on their most recent, lagged value of DSOP. We then investigate, within each quantile bin, the firms' ex-post return during the month of their release of their quarterly earnings announcement. Recall that DSOP measures the relative outperformance of downstream industries over upstream industries over the firm's fiscal quarter. If investors initially attach undue weight to the accounting composition of a firm, and only learn ex-post that the firm's factual industry exposure is tilted towards downstream industries then we expect that DSOP is positively correlated with ex-post returns of the verticlly integrated firm. This effect should be most prevalent when events in upstream and downstream industries diverge drastically, and hence DSOP takes on extreme negative or positive values.

To begin, Figure 2 presents graphical evidence of the effect only for the most extreme deciles of DSOP firm-quarters. The plot shows the daily cumulative abnormal returns (CAAR) over a 4-Factor model ((Fama and French, 1993), (Carhart, 1997)) in windows around the date of quarterly earnings announcements. Factor exposures are estimated over a [-135,-11] trading day window prior to the announcement date.[15] 95% confidence intervals are based on standard errors computed using standard event-study methodology (Campbell, Lo, and MacKinlay, 1997).

Figure 2 here

It is clearly visible from Figure 2 that the DSOP sorting variable has strong predictive power for the returns of vertically integrated firms. Firms whose downstream industry outperformed its upstream industry over the preceeding quarter display a large positive abnormal return of roughly four percentage points over the plotted time window. Part of this abnormal return stems from a jump around the announcement days, in line with a positive announcement surprise. In contrast, firms whose downstream industry underperformed display a return that is practically equal to zero. Most importantly, the *difference* between the two groups is large and significant, and in the predicted direction. In line with the notion that investors predictably revise their expectations towards the downstream industry portfolio, the tenth DSOP decile outperforms the first DSOP decile.

One very salient feature of Figure 2 is the strong asymmetry of the effect. It appears that positive DSOP values have predictive power whereas negative values do not. Afterall, the negative DSOP group shows insignificant abnormal returns over the period.

While we cannot explain this asymmetry with certainty, we want to point out that the above conclusion may be premature. The reason is that returns around earnings announcements in general have been documented to be 'abnormally' positive when judged against standard factor models. Ball and Kothari (1991), for instance, find a significant positive

[15]The release dates of quarterly earnings are taken from the Compustat quarterly database and complemented with the release dates on I/B/E/S. When both are available, we take the earlier date following DellaVigna and Pollet (2009), who report that for periods after 1990, the earlier of the two almost always corresponds to the correct announcement date as identified by searching newswires.

two-day announcement premium of 0.24% between 1980 and 1988, Cohen, Dey, Lys, and Sunder (2007) document a premium of 0.11% for a sample of firms between 1989 and 2001, and Lamont and Frazzini (2007) document a monthly premium of almost one percentage point over firms' announcement month between 1973 and 2004. Whether one concludes the predictabilit effect in Figure 2 to be asymmetric or not thus heavily depends on the benchmark one uses to judge normal returns. If one were to adjust the decile plots for the average performance of firms in their announcement month, the effect would appear less asymmetric. The important takeaway from Figure 2 is that extreme values in lagged DSOP induce a significant *difference* between ex-post returns.

To provide more detail about the magnitude and robustness of the effect, we next show some numerical results. Table 4 shows abnormal returns similar to those plotted on a daily basis above, however now on a quintile basis and for several subgroups of firms in our dataset.[16] The first row shows the cumulative abnormal returns for all firms that our classification mechanism deemed vertically integrated - i.e., the same set of firms used in the plot above. The second row provides the equivalent abnormal returns for the set of multi-segment firms that our classification mechanism could not assign to either forward or backward integrated groups. This set essentially serves as a control group in this table, akin to a placebo regression. Rows three and four respectively show results separately for only forward and only backward integrated firms. All CAARs are for the time window [-5,10] around the announcement day, and all t-statistics shown are based on robust standard errors clustered by firm and year.

Table 4 here

As could be expected, the results from the extreme quintiles in the first row are similar to those of the figure above. The extreme DSOP quintile (downstream outperfomed) has an abnormal announcement return that is economically and statistically larger than that of the first quintile (downstream underperformance). For intermediate quintiles, the returns are non-monotonic. The predictability only arises for extreme differences between upstream and downstream industry returns.

Note that the results look strikingly different for the set of firms in row 2 that our

[16] Results on a decile, instead of a quintile, basis are highly statistically significant for the first and tenth deciles, as can be expected based on Figure 2, and lead to the same conclusions.

classification mechanism did not assign vertical integration status. Recall that these are firms with non-zero values of our vertical integration score $VERT$, which were small in absolute terms as judged by the cross-section. For these firms, no visible pattern across DSOP quintiles can be detected at all. Importantly, the extreme quintiles 1 and 5 show no significant difference as those of integrated firms. To the extent that the firms in this group are either *not* vertically integrated, or the low (albeit nonzero) value of $VERT$ is misleading with respect ot the direction of vertical integration, this is a non-finding we would expect. In addition, the non-finding for this group is reassuring in the sense that our results for vertically integrated firms do not seem to arise for arbitrary sets of firms. This makes it unlikely that some alternative story, such as industry momentum, is responsible for our findings. Finally, rows three and four present the results for backward and forward integrated subsamples separately. The general effect holds up for each subgroup, although the statistical significance drops for the group of forward integrated firms.

Since all firms in our sample have one very dominant segment, one could suspect that either (a) our weigthing of industries in DSOP along with some form of industry momentum may be driving our results or (b) investors are simply more attentive to the salient industry news that affects the large segments of multi-segment firms and hence react with a lag to small-segment industry news. Both these concerns are largely mitigated by the results in rows three and four. Recall that forward integrated firms (row 3) have *small* downstream segments, wheras backward integrated firms (row 4) have *large* downstream segments. The fact that we see parallel results for both subsets thus makes it unlikely that either (a) or (b) are the driving forces behind our findings.

4.3 Placebo Industry Returns

One concern with our results might be that they could emerge from industry momentum, which is unrelated to the particular industry exposure of vertically integrated firms. Moskowitz and Grinblatt (1999) have documented that there exists a strong momentum effect in industry portfolios. Are we merely picking up industry momentum in our sample of vertically integrated firms? The fact that we use differences between downstream and upstream industry portfolios as a predictive variable makes this story unlikely, as does the fact that the predictability pattern only holds up for vertically integrated firms in our sample and not for multi-segment firms without a vertically integrated structure. Nevertheless, as an additional robustness check, we next perform a simple placebo analysis.

In particular, we replace the announcement return of vertically integrated firms, that was the variable of interest in the previous section by the CAAR (measured over the same time period) of a placebo industry porfolio composed of single-segmented firms. The firms are the same firms that enter the upstream and downstream industry portfolios used to compute $DSOP$. However, now their returns are weighted by the vertically integrated firm's segment weights, such as to form a joint industry portfolio representative of the overall industry composition of the vertically integrated firm. If our results in the previous section are driven by industry momentum, then we should also pick up this momentum effect in the returns of this industry portfolio.

Table 5 shows the results of performing the exact same sorts as in the previous section, but now on the placebo portfolio's return. The first row shows that the CAAR of the placebo portfolio cannot be predicted by the downstream outperformance for the vertically integrated firms. The results of row two confirm that this is neither the case for firms which we do not classify as vertically integrated. A further separation of this test for backward and forward integrated firms, as presented in rows three and four, does not alter the conclusion.

Table 5 here

5 Self-Financing Trading Strategies

In this section, we analyze whether the predictability effect documented in the previous section gives rise to profitable trading strategies that could have been implemented by informed investors based on available information.

What makes our setting slightly non-standard relative to other trading strategies explored in the literature, is that our analysis has focused exclusively on the time periods surrounding the quarterly release of accounting data. We choose to retain this focus because the quarterly announcement period is a period in which we can reasonably expect investors to learn about previous judgment mistakes. To do so, we construct a monthly trading strategy that only uses firms with upcoming earnings announcements in the month to come. That is, at the beginning of each month, we retain *all* multi-segment firms in our sample with upcoming earnings announcements and sort these firms according to their degree of downstream outperformance to assign them to long and short portfolios.[17]

In parallel with our earlier procedure, we want to assign all vertically integrated firms with positive values of downstream outperformance to a long portfolio and those with negative values to a short portfolio. One complication that arises is that we cannot rely on our earlier classification of firms into forward and backward integrated. Recall that our cross-sectional analysis in the previous sections focused mainly on two subgroups of firms in our sample that we assigned vertical integration status. Here we cannot restrict our attention to these particular subgroups because investors lacked the cross-sectional information we used to assign firms to these groups - in particular the ranking of a firm's $VERT$ relative to other firms in our dataset. To avoid using this information, we construct a simple variation of our previous DownStream OutPerformance measure. For each multi-segment firm i we simply compute

$$DSOP2_{i,t} = |VERT_i| * DSOP_{i,t} = |VERT_i| * [R_{i,t}^{downstream} - R_{i,t}^{upstream}] * w_i^S \qquad (4)$$

where $VERT_i$ is a firm's vertical integration score based on BEA data, just as before. Since $VERT_i$ captures our degree of confidence that firm i is indeed vertically integrated, the multiplication by the absolute value of $VERT$ simply has the desired effect of weighting the degree of industry divergence $DSOP_{i,t}$. For two firms with equal downstream and upstream industry patterns (captured by DSOP), we assign larger weight to the firm for which we are more confident about its industrial structure.

Given the new sorting measure, we proceed to construct monthly portfolios following a simple sorting algorithm. At the beginning of each month we rank all firms with upcoming announcements according to their past-fiscal-quarter value of DSOP2. We allocate firms with a below-median value of this sort (downstream industries underperformed) to a short

[17]One caveat of this algorithm is that it may not always be known with certainty to investors at the beginning of a calendar month whether a certain firm will be reporting quarterly results within the upcoming month. Although scheduled announcement dates are usually known in advance, Cohen, Dey, Lys, and Sunder (2007) and Lamont and Frazzini (2007) stress that actual announcements can occur early or late relative to scheduled announcements. In using ex-post realized announcement dates in forming portfolio strategies, one thus uses information unknown to the investor at the time of trading, rendering the strategy impractical in reality. We stay agnostic to this issue and refer to Lamont and Frazzini (2007) who find that simple algorithms can predict the announcement month with large accuracy and that portfolio returns are thus similar using actual or predicted announcement months.

portfolio, and firms with an above-median value (downstream industries outperformed) to a long portfolio. We then compute the monthly returns on these two portfolios either by equal-weighting or value-weighting the component returns. Finally, the self-financing strategy consists of buying the long portfolio and selling the short portfolio simultaneously.[18]

Table 6 describes the monthly returns for the resulting long, short, and self-financing (long-short) portfolios across our sample period. First, Panel A reports information for portfolio excess returns. The mean excess return over the announcement month is 1.9% for firms in the long portfolio (downstream outperformance) and 0.49% for the short portfolio (downstream underperformance). A self-financing strategy that exploits this return difference earns almost 1.433% per month with a sharp ratio of 0.17 (0.6 annualized).

Since the returns in Panel A are bare excess returns without adjustment for risk, an obvious concern is that the large return differences between long and short portfolios may be due to differences in systematic risk or exposure to other well-known return factors. To address this concern, we next adjust the returns from our trading strategies for the standard risk-factors used in the literature. In particular, in Panel B of Table 6, we take the monthly returns from before and regress them on the monthly excess market return (MktRf), Fama and French (1993) factors (SMB and HML), Carhart (1997)'s momentum factor (MOM).[19] The table reports the resulting four-factor alpha in the first column, along with the remaining factor loadings in columns two to five. t-statistics are shown in paretheses.

Table 6 here

Overall, the control for risk-factors has little effect on our findings. Although the long and short portfolios individually have significant factor loadings on the risk-factors, their individual exposure is similar in magnitude. As a result, the composite self-financing strategies show little factor exposure.

An exception is the HML factor in the value-weighted case, which emerges from the short value-weighted portfolio. This portfolio thus seems to include an unproportionally

[18]Other studies have sorted into finer quantiles, such as quartiles or quintiles, for the purpose of computing portfolio returns. While we would like to do so, our cross-sectional sample size keeps us from doing so in two thirds of the months of the year. Table 8 in the Appendix details the number of firms entering the trading strategy across our sample period. Whereas April, July, October, January and February tend to be months with many observations, sample size is very small in 'off-season' months, i.e., months outside the typical reporting seasons. Because of this, any sorting into finer bins quickly becomes impractical, with portfolio size dropping below reasonable values.

[19]The monthly market, value, size, and momentum factors are all obtained from Kenneth French's website.

high number of high book-to-market returns. Because these firms tend to show abnormally large returns according to Fama and French, their addition to our short portfolios is actually playing against the performance of the value-weighted portfolio performance in an un-adjusted excess-return sense. As a result, the value-weighted long-short strategy has a negative HML factor loading. Adjusting for this exposure has the effect of increasing, rather than decreasing, the alpha in the value-weighted case over and above the associated mean excess return.

Overall, the alphas of both value- and equal-weighted long-short strategies are economically large and highly statistically significant. In the equal-weighted case, the portfolio earns a monthly abnormal return of 87.3 basis points (t-stat 2.15). The value-weighted portfolio earns an abnormal return of 1.79% (t-stat 3.29), which corresponds to an annualized return of roughly 20%.[20]

Finally, to address concerns that the trading strategy may be arising from a particular sub-period from our sample, we plot the cumulative abnormal return (alpha) of the weighted Long/Short strategy in Figure 3. The strategy appears to be generate consistent returns over the sample period. This fact is also important because the number of firms in our trading strategy varies considerably from month to month. Our strategy contains a large number of firms in typical reporting months (i.e., January, April, July, and October), but sometimes drops to low firm numbers is off-season months.[21] The fact that returns appear stable both within calendar quarters and across sample years is reassuring.

6 EPS Forecast Errors

Taken as a whole, our results so far indicate significant predictability of equity returns. The relationship between lagged industry return patterns (DSOP) and subsequent returns of vertically integrated firms is in line with a misjudgement of the relevance of industry news by investors and subsequent learning about the actual impact. A question that naturally arises is which market participants fall trap to the particular industry exposure of vertically integrated

[20]In the years between 1984 and 1989, sample size sometimes drops below a thresholds of two firms, such that no trading is possible at all in some months. In total, our trading strategy is active in 273 month out of 288 available months in the 24 years between 1984-2007. The monthly abnormal return of 1.787% is thus roughly comparable to an annualized return of 20.3% ($= 1.787\% * 12 * \frac{273}{288}$).

[21]Table 8 in the Appendix details the number of firms entering the Long and Short Portfolios on a monthly basis.

firms. Expert investors with specialized knowledge about the industries and production processes of vertically integrated firms surely should not be mislead by the confounding industry dynamics we use to predict returns.

In this section, we investigate to which extent a particular group of market participants, security analysts, make the judgement mistakes that we claim underly the return predictability we have documented. Since our empirical setup focuses exclusively on the time period around firm's quarterly earnings announcements, we can study the quarterly forecasts of security analysts in the exact same setup that we used to study announcement returns in earlier sections.

To do so, we collect earnings forecast data from the I/B/E/S details files to compute a consensus forecast, that reflects the aggregate opinion of analysts that actively follow the company. We restrict our analysis to forecasts made by analysts with multiple forecasts for the same firm-quarter. Out of these, we keep the last EPS forecast made around the end of the fiscal quarter. In particular, we require that the forecast needs to be issued at maximum 45 days before the fiscal quarter end or, alternatively, between the fiscal quarter end and the announcement date. Furthermore, we delete a forecast if it is issued after the earnings announcement date or, following Hong and Kacperczyk (2010), if the forecast deviates from the actual earnings by more than \$ 10. Based on the remaining forecasts, we follow the literature and compute one single consensus forecast per firm and quarter as the median of all outstanding forecasts. We define the forecast error as the difference between the firm's realized EPS and the consensus forecast, standardized by the stock price recorded at the end of the previous fiscal year end

$$FE = \frac{EPS - FORECAST}{STOCK\ PRICE}. \tag{5}$$

Given this measure of consensus forecast errors, we test whether analyst forecasts include a predictable error in the same direction as equity returns do. If analysts make the hypothesized judgement mistake, we expect forecasts to be exceedingly optimistic following downstream underperformance and pessimistic following downstream outperformance. To test this, we follow the same sorting procedure we applied before for the purpose of testing return predictability. We take all firm-quarters of all forward and backward integrated firms in our dataset (i.e., firms with above median positive levels of $VERT$ or below median negative levels) and sort them according to their value of $DSOP_{i,t}$, i.e. downstream industry outperformance. Table 7 shows the average forecast error per quintile bin of this sort.

Table 7 here

For vertically integrated firms (row 1), the pattern across bins is indeed in line with a misjudgement of industry shocks. Consensus forecast errors are increasing across the five bins, suggesting that downstream outperformance is associated with abnormally large forecaste errors (i.e., abnormal pessimism in forecasts). Downstream underperformance is associated with abnormally small forecast errors (i.e., abnormally small pessimism in forecasts). This pattern is precisely in line with the notion that analysts (as judged by their consensus voice) are agnostic to the inflated exposure to downstream industry shocks of vertically integrated firms. The difference between quintiles one and five is significant with a t-statistic of 2.23 (based on standard errors clustered at the firm and month level). As in the return analysis, the second row shows that the pattern found for vertically integrated firms does not hold up for the set of firms that we cannot assign to either the forward or backward intgrated group based on BEA data.

The results of the last two columns show that the significant effect in row 1 arises mainly from backward integrated firms in our dataset. For these, the predictability of forecast errors is statistically significant and in the expected direction. For the subset of forward integrated firms, the effect is only weak. Although forecast errors are on average slightly higher in bin five than in lower bins, as predicted, the effect is insignificant at conventional confidence levels.

In unreported robustnest checks, we repeat our analysis based on non-parametric tests for differences in medians or ranks of forecast errors. These tests suggest that the above documented effect is driven by extreme forecast errors, however. We believe the results to be of interest nevertheless to the extent that extreme forecast errors are likely to be also associated with most extreme stock price reactions.

7 Conclusion

This paper documents return predictability for vertically integrated firms. Because vertically integrated firms are more heavily exposed to downstream industry shocks than is implied by the size of downstream segments in an accounting sense, we argue that these firms represent an interesting sample to test the market's efficiency in incorporating industry news into stock prices. We find that stock returns of vertically integrated firms feature a predictable component in the firms' months of quarterly earnings announcements. The effect appears economically large. Trading strategies designed to exploit the effect generate annual abnormal returns as high as 20%. Moreover, we document that analyst forecasts for quarterly EPS include a predictable error in the same direction as stock price predictability.

Taken as a whole, the findings suggest that market participants fail to incorporate the effects of intersegment customer-supplier links in their valuation of vertically integrated firms. This finding extends existing research that has shown that customer-supplier links between firms, industries, and countries lead to cross-predictability effects. The fact that our findings are based on links *within* a single firm, sheds new light on the economic channel underlying existing cross-predictability findings. In particular, it suggests that investors fail to *understand* the consequences of economic links or their magnitude, much rather than failing to observe news outside their center of attention.

A Data Screening

Our analysis uses all segments classified as business segment ($STYPE$ = Busseg) or operating segment ($STYPE$ = Opseg) listed in the Compustat Segment tapes between 1979 and 2007 and firm data from the CRSP-Compustat merged database over the same period. For the Segments database, we only use entries whose source year (srcyr) equals the calendar year of the entry, to assure we only use data as initially reported (i.e., no restated data) and to avoid double counting of firms.

We drop firm-years if any of the following conditions are met: firm sales, firm assets, or market capitalization are missing (where market capitalizations are computed as the product of shares outstanding and fiscal year ending price); firm sales or market cap. are below $20 Million or firm assets are negative; the fiscal-year end share price falls short of $1 (penny stocks); any of the firm's segments is classified as financial segment by Compustat (SIC between 6000 and 6999); the sum of segment sales deviates by more than 1% from firm sales; the company is a pure holding company.

In addition to the above, a firm must have non-missing SIC codes and segment-level sales for all segments reported in the Compustat Segments tapes that truly appear to be operating segments. Problematically, the Compustat Segment tapes frequently list expenses for firm headquarters or intersegment eliminations as separate segments. These typically have missing industry codes as they are not associated with a single firm segment (and frequently negative sales). To avoid dropping firms with such overhead segment entries, we eliminate the individual overhead segment before screening based on segment sales and SIC availability.

First, we drop segments where Compustat has assigned its variable *sid* a value of 99. According to Compustat, these represent intersegment eliminations. We then search the textual segment descriptions for the words "overhead", "eliminations" and common misspellings of the same expressions, and delete entries with problematic industry and sales values whose descriptions seem unambiguous. After this screening of the individual segment entries, we drop firm-year observations if a firm has a missing segment SIC code or negative (or missing) segment sales for any one of the remaining segments reported.

References

Baker, Malcolm, Richard S. Ruback, and Jeffrey Wurgler, 2007, Behavioral corporate finance: A survey, in Espen Eckbo, ed.: *Handbook in Corporate Finance: Empirical Corporate Finance* vol. 1.

Ball, Ray, and S. P. Kothari, 1991, Security returns around earnings announcements, *The Accounting Review* 66, 718–738.

Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavioral finance, in G.M. Constantinides, M. Harris, and R. M. Stulz, ed.: *Handbook of the Economics of Finance*vol. 1 of *Handbook of the Economics of Finance* . chap. 18, pp. 1053–1128 (Elsevier).

Bartov, Eli, and Gordon M. Bodnar, 1994, Firm valuation, earnings expectations, and the exchange-rate exposure effect, *The Journal of Finance* 49, 1755–1785.

Berger, Philip G., and Eli Ofek, 1995, Diversification's effect on firm value, *Journal of Financial Economics* 37, 39 – 65.

Campbell, John Y., Andrew Wen-Chuan Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton Univ. Press: Princeton, NJ) 2. print. with corrections edn.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Cohen, Daniel A., Aiyesha Dey, Thomas Z. Lys, and Shyam V. Sunder, 2007, Earnings announcement premia and the limits to arbitrage, *Journal of Accounting and Economics* 43, 153 – 180.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *The Journal of Finance* 63, 1977–2011.

Cohen, Lauren, and Dong Lou, 2010, Complicated information processing, *HBS working paper.*

DellaVigna, Stefano, and Joshua M. Pollet, 2007, Demographics and industry returns, *The American Economic Review* 97, 1667–1702.

——— , 2009, Investor inattention and friday earnings announcements, *The Journal of Finance* 64, 709–749.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics.*

Fan, Joseph P H, and Larry H P Lang, 2000, The measurement of relatedness: An application to corporate diversification, *Journal of Business* 73, 629–60.

Gilson, Stuart C., Paul M. Healy, Christopher F. Noe, and Krishna G. Palepu, 2001, Analyst specialization and conglomerate stock breakups, *Journal of Accounting Research* 39, 565–582.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297 – 331.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics, forthcoming.*

Hong, Harrison, and Jeremy C. Stein, 2007, Disagreement and the stock market, *Journal of Economic Perspectives* 21, 109–128.

Hong, Harrison, Walter Torous, and Rossen Valkanov, 2007, Do industries lead stock markets?, *Journal of Financial Economics* 83, 367 – 396.

Hou, Kewei, 2007, Industry Information Diffusion and the Lead-lag Effect in Stock Returns, *Rev. Financ. Stud.* 20, 1113–1138.

Huberman, Gur, and Tomer Regev, 2001, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *The Journal of Finance* 56, 387–396.

Lamont, Owen, and Andrea Frazzini, 2007, The earnings announcement premium and trading volume, *NBER Working Paper No. 13090.*

Menzly, Lior, and Oguzhan Ozbas, 2006, Cross-industry momentum, *Working Paper, University of Southern California.*

——— , 2010, Market Segmentation and Cross-Predictability of Returns, *The Journal of Finance, Forthcoming.*

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of Finance* 54, pp. 1249–1290.

Palomino, Frederic, Luc Renneboog, and Chendi Zhang, 2009, Information salience, investor sentiment, and stock returns: The case of british soccer betting, *Journal of Corporate Finance* 15, 368 – 387.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563 – 602.

Ramnath, Sundaresh, 2002, Investor and analyst reactions to earnings announcements of related firms: An empirical analysis, *Journal of Accounting Research* 40, 1351–1376.

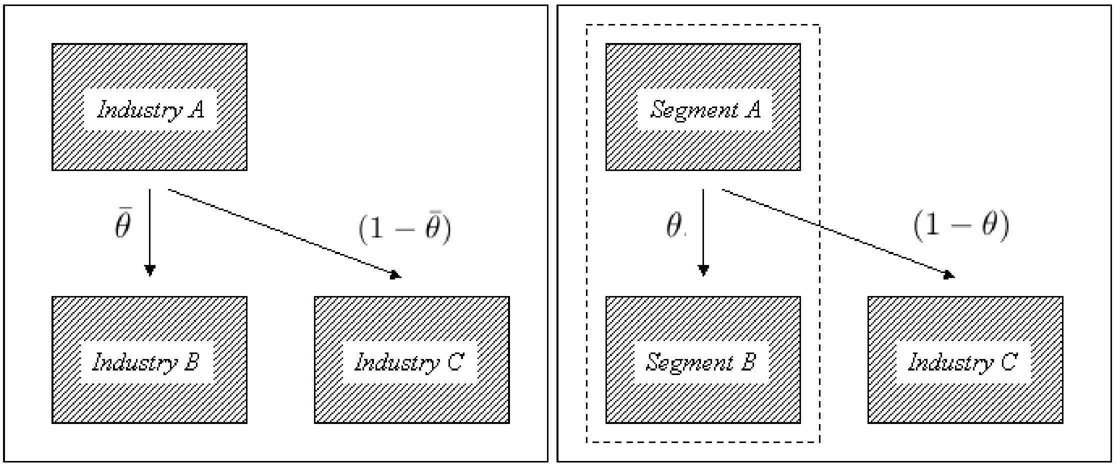
Rizova, Savina, 2010, Predictable Returns of Economically Linked Countries: Evidence and Explanations, *Working Paper, University of Chicago.*

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52, pp. 35–55.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *Journal of Business* 75, 583–608.

Figure 1: **Segment Industry Exposure: A stylized graphical representation.** The figure depicts the inter-industry sale of goods (*Panel A*) and the inter-segment sale of goods within the vertically integrated firm (*Panel B*).



Panel A: Industry representative firms
Panel B: A vertically-integrated conglomerate

Figure 2: **Vertically Integrated Firms: Daily Abnormal Returns around the Quarterly Earnings Release**. The figure plots daily cumulative average abnormal returns (CAARs) in the 25 trading days around firm's quarterly earnings announcements (td = 0) for two groups of firms. The top line represents forward and backward integrated firms whose downstream industries outperformed its upstream industries over the most recent fiscal quarter (DSOP decile 10). The bottom line represents firms whose downstream industries underperformed its upstream industries (DSOP decile 1). Only firms assigned backward or forward integrated status (see text) enter the figure. Abnormal returns are over a four-factor model, estimated over the window [-135,-11]. Shaded regions represent 95% confidence intervals based on standard event-study standard errors (Campbell, Lo, and MacKinlay, 1997).

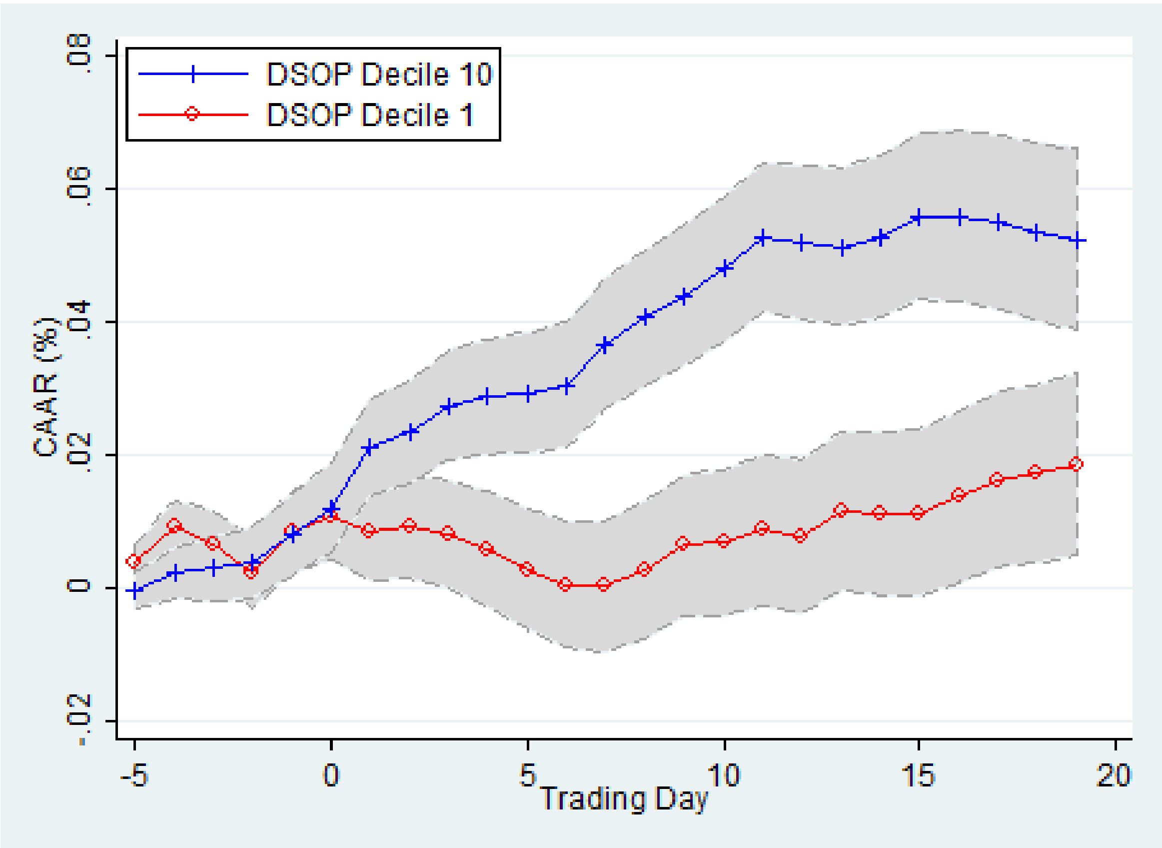


Figure 3: **Cumulative Alpha over the Sample Period** The figure plots the cumulative monthly abnormal return over a four factor model (alpha) arising from the value-weighted long/short strategy. On the first day of each month, we construct portfolios from all firms with upcoming earnings announcements during the month. The firms are sorted according to the product $|VERT_i| * DSOP_{i,t}$ - i.e., according to the differential between lagged upstream and downstream industry returns, weighted by the firm's degree of vertical integration (See the text for details). The short portfolio sells firms with below-median values of the product (i.e., firms whose downstream industries underperformed). The long portfolio buys firms with above-median values (firms whose downstream industries outperformed). Portfolios are held throughout a month and then reformed using the next set of reporting firms.

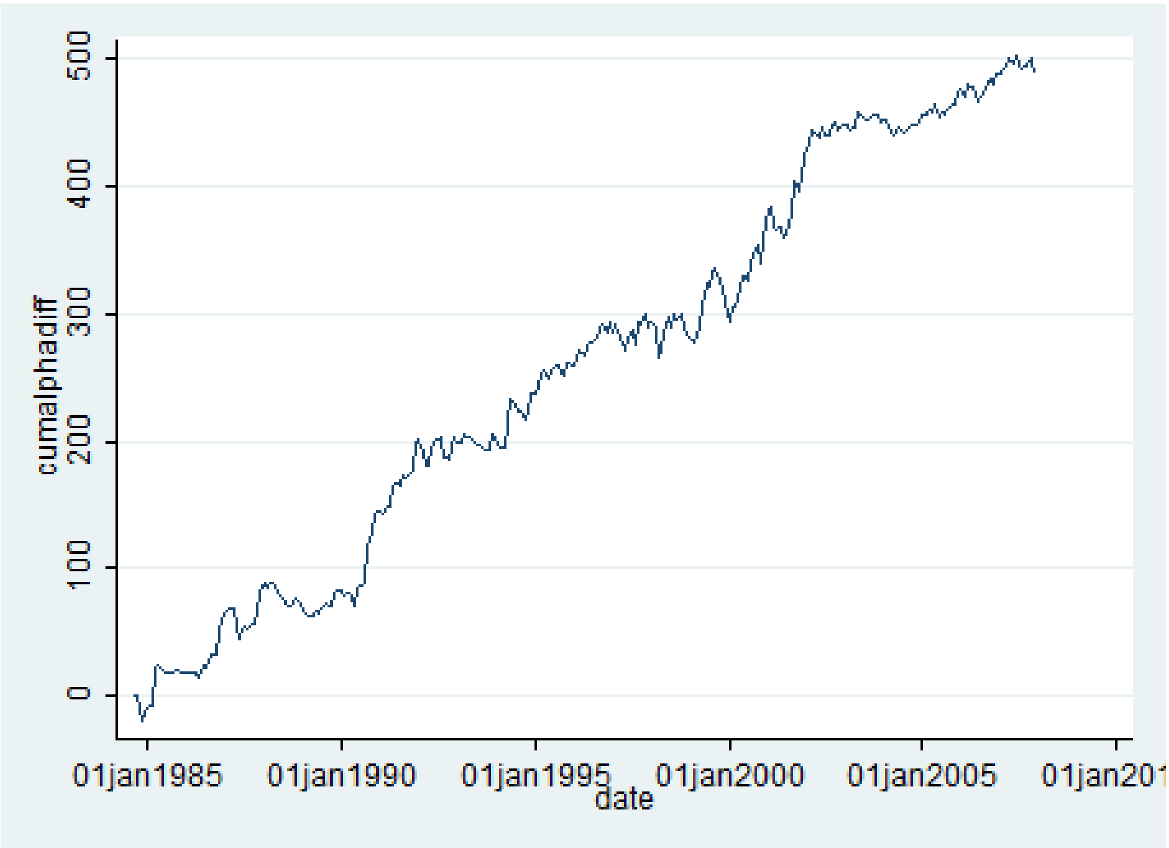


Table 1: **Summary Statistics**
The table shows summary statistics for the multi-segment firms that enter our final sample for trading purposes. Each observation refers to a firm-quarter between 1984 and 2007. Panel A includes all firms with non-missing non-zero vertical integtration score $VERT$. Panels B and C, respectively include only firms that we classify as backward and forward integrated for the purpose of cross-sectional analyses. Backward integrated are all firms with above median positive vertical integration score. Forward integrated are all firms with below median negative vertical integration score. The variables are defined as follows. MktCap denotes firms stock market capitalization, computed as the product of common shares outstanding (Compustat item *csho*) and fiscal year-end share price ($prcc_f$). Assets are total year-end book assets (*at*). Sales are total net sales (*sale*). Market/Book is the market to book ratio, computed as MktCap and total debt divided by assets. Market/Sales is the market to sales ratio, computed as MktCap and total debt divided by Sales. We define total debt as the sum of long-term debt (*dltt*), debt in current liabilities (*dlc*) and preferred stock redemption value (*pstkrv*). ROA is a firm's quarter-on-quarter change in Return on Assets, where ROA is computed as the sum of net income (*ibq*) and depreciation and amortization (*dpq*) divided by assets (*atq*). Number of Segments refers to the number of non-overhead business segments with differing four-digit SIC codes reported in the Compustat Segments database. The distribution of ROA is truncated at the 1% level. VERT is a firm's vertical integration score, computed from a firm's industry-specific sales and inter-industry statistics from the U.S. Bureau of Economic Analysis about the aggregate flow of goods between industries (see the text for details). DSOP measures DownStream OutPerformance over the fiscal quarter - that is, the relative outperformance of a stock portfolio the firm's downstream industry peers over a stock portfolio of the firm's upstream industry peers over the fiscal quarter (see the text for details). CAR[-5,10] is the cumulative abnormal return of the firm's stock over a fifteen-day time window around the firm's quarterly earnings release date. The abnormal return is with respect to a four-factor model estimated over the window [-135,-11] on daily data.

Panel A: All Quarterly Observations, 1984 - 2007						
	Median	Mean	StdDev	25%	75%	Obs.
MktCap (Million USD)	741	3,732	13,941	275	2,452	9,735
Assets (Million USD)	877	3,368	9,139	299	2,634	9,735
Sales (Million USD)	1,008	3,304	10,050	321	2,552	9,735
Market/Book	1.143	1.487	1.135	0.867	1.674	9,735
Market/Sales	1.199	1.794	2.720	0.734	2.075	9,735
Number Segments	2	2.264	0.525	2	2	9,735
Δ ROA*100	0.026	-0.027	1.335	-0.515	0.500	6,711
VERT*100	0.019	0.742	6.562	-0.289	0.583	9,735
DSOP*100	0	0.118	3.924	-0.892	1.005	9,735
Announcement Return[-5,10]*100	0.526	0.769	11.741	-4.976	6.405	9,735

Table 2: **Summary Statistics continued**

Panel B: Quarterly Observations of Backward Integrated Firms, 1984 - 2007						
	Median	Mean	StdDev	25%	75%	Obs.
MktCap (Million USD)	781	3,350	10,897	285	2,385	2,651
Assets (Million USD)	939	3,768	9,915	379	3,134	2,651
Sales (Million USD)	1,107	2,927	7,230	378	2,675	2,651
Market/Book	1.041	1.378	1.003	0.832	1.533	2,651
Market/Sales	1.190	1.648	1.544	0.758	1.983	2,651
Number Segments	2	2.274	0.569	2	2	2,651
Δ ROA*100	0.016	-0.030	1.393	-0.579	0.511	1,855
VERT*100	2.110	5.350	9.901	0.930	5.151	2,651
DSOP*100	0	0.168	4.057	-0.873	0.998	2,651
Announcement Return[-5,10]*100	0.400	0.713	11.357	-4.886	6.026	2,651

Panel C: Quarterly Observations of Forward Integrated Firms, 1984 - 2007						
	Median	Mean	StdDev	25%	75%	Obs.
MktCap (Million USD)	618	2,683	10,078	193	1,840	2,214
Assets (Million USD)	746	2,893	11,409	236	1,931	2,214
Sales (Million USD)	830	2,691	6,201	241	2,145	2,214
Market/Book	1.119	1.397	1.008	0.840	1.577	2,214
Market/Sales	1.065	1.774	3.046	0.615	2.108	2,214
Number Segments	2	2.297	0.547	2	3	2,214
Δ ROA*100	0.026	-0.023	1.224	-0.446	0.467	1,517
VERT*100	-1.360	-3.205	5.459	-3.554	-0.733	2,214
DSOP*100	0	-0.084	2.984	-0.821	0.811	2,214
Announcement Return[-5,10]*100	0.632	0.987	12.420	-5.153	6.808	2,214

Table 3: **Fundamental Upstream and Downstream Industry Exposure.** This table presents regressions of quarterly changes of a vertically integrated firm's return on assets on the contemporaneous ROA changes of baskets of industry-matched single-industry firms. Only firms classified as forward or backward integrated enter the regression. ΔROA^{DOWN} represents the firm's downstream industries, $\Delta\text{ROA}^{WEIGHTED}$ a weighted average of all the firm's industries, and $\Delta\text{ROA}^{MARKET}$ a market-wide ROA change based on all stand-alone firms in all industries. We calculate industry ROA changes as equal-weighted averages of all single-segmented firms ROA changes with matching four-digit SIC code and overlapping fiscal-quarter definition. All distributions are truncated at the 1% level. Standard errors, shown below coefficient estimates, are clustered by firm and by reporting year where indicated. Asterisks indicate significance at the 10%(*), 5%(**), and 1%(***), respectively.

		ΔROA_{FIRM}*100		
ΔROA^{DOWN}		0.125	0.128	0.137
		(0.042)***	(0.04)***	(0.042)***
$\Delta\text{ROA}^{WEIGHTED}$	0.272	0.174	0.185	0.168
	(0.057)***	(0.053)***	(0.051)***	(0.052)***
$\Delta\text{ROA}^{MARKET}$	0.114	0.096		0.032
	(0.082)	(0.085)		(0.085)
Constant	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year & Firm Clustered	yes	yes	yes	no
Firm Fixed Effects	no	no	no	yes
Observations	3107	3107	3107	3107
R^2	0.021	0.024	0.024	0.023
F statistic	22.657	16.258	23.344	21.22

Table 4: **Announcement-Period Returns by Downstream Industry Outperformance** The table reports cumulative average abnormal returns (CAARs) within five quintile bins of stocks over the [-5,10] day window around firm's quarterly earnings release dates. Abnormal returns are over a four-factor model estimated on daily returns over the window [-135,-11] relative to the eanings release. Bins are formed by allocating stocks to quintiles based on their most recent value of DSOP - the downstream outperformance measure (see the text for details). Downstream outperformance stocks are placed in high quintiles, stocks with downstream underperformance in low quintiles. The sorts are done separately for firms classified as forward integrated, backward integrated, and not vertically integrated. The t-statistics reported in column eight correspond to the difference in mean CAARs between fifth and first DSOP quintlies and are based on standard errors clustered by stock and year.

	Downstream Outperformance						
	Q 1	Q 2	Q 3	Q 4	Q 5	(5-1)	t-value
FORWARD+BACKWARD	0.43	0.85	0.71	0.53	1.67	1.24	2.50
NOVERT	1.01	0.24	0.40	1.18	0.67	-0.35	-0.87
FORWARD	0.76	0.86	0.73	0.69	1.89	1.13	1.40
BACKWARD	0.15	0.84	0.69	0.40	1.48	1.33	2.18

Table 5: **Abnormal Returns of Matched Industry Portfolios over the Announcement Period** The table reports the cumulative abnormal returns (CAARs) of sets of *placebo* portfolios over the same fifteen-day intervals that were studied in Table 4. For each multi-segment firm-quarter entering the analysis above, a portfolio of single-segment firms is formed such that it represents the industry composition of the multi-segment firm. The returns on these portfolios are recorded over the same [-5,10] day windows around the multi-segment firm's quarterly release dates. The table shows the CAARs resulting for the same bins that were used in Table 4. As before, abnormal returns are over a four-factor model, estimated over the time window [-135,-11] and standard errors are clustered by firm and year.

	Downstream Outperformance						
	Q 1	Q 2	Q 3	Q 4	Q 5	(5-1)	t-value
FORWARD+BACKWARD	0.51	0.27	0.66	0.28	0.51	-0.00	-0.01
NOVERT	0.37	0.14	0.54	0.53	0.51	0.15	0.95
FORWARD	0.62	0.43	0.59	0.34	0.23	-0.39	-1.14
BACKWARD	0.42	0.13	0.73	0.22	0.74	0.32	1.05

Table 6: **Monthly Trading Strategies** The table reports statistics of monthly returns generated by portfolios that buy and sell the stocks of vertically integrated firms during their announcement month. On the first day of each month, we construct portfolios from all firms with upcoming earnings announcements during the month. The firms are sorted according to the differential between lagged downstream and upstream industry returns, weighted by the firms' degree fo vertical integration. (The sorting measure is $|VERT_i| * DSOP_{i,t}$; see the text for details.) Below-median firms, whose downstream industry underperformed during the past fiscal quarter, are assigned to the short portfolio. Above-median firms, whose downstream industries outperformed, are assigned to the long portfolio. Portfolios are held throughout a month and then reformed using the next set of reporting firms. Panel A shows statistics for the resulting monthly excess returns of a value-weighted portfolio. Panel B shows results from regressing monthly excess returns on the CRSP market excess return (MktRf), Fama-French SMB and HML, and Carhart MOM factors. t-statistics are reported in parentheses.

Panel A: Summary Statistics Value-Weighted Returns

	Long	Short	Long-Short
Mean	1.925	0.492	1.433
t-statistic	4.464	1.175	2.851
StdDev	7.126	6.916	8.307
Skewness	0.347	-1.269	0.649
Kurtosis	4.491	8.356	5.738
SharpeRatio	0.27	0.071	0.173

Panel B: Factor Loadings, Trading Strategy 1985-2007

	Alpha	MktRf	SMB	HML	MOM	R2
Long (eq)	1.307	1.004	0.535	0.288	-0.030	0.446
	(4.481)	(12.497)	(5.196)	(2.187)	(-0.354)	
Short (eq)	0.434	1.142	0.714	0.573	-0.122	0.576
	(1.540)	(13.605)	(6.563)	(5.026)	(-1.997)	
Long/Short (eq)	0.873	-0.139	-0.179	-0.285	0.093	0.018
	(2.151)	(-1.191)	(-1.207)	(-1.738)	(0.998)	
Long (vw)	1.422	0.846	-0.001	0.002	-0.034	0.259
	(3.875)	(9.147)	(-0.011)	(0.01)	(-0.310)	
Short (vw)	-0.365	1.082	0.238	0.485	-0.0008	0.376
	(-1.023)	(9.767)	(1.622)	(3.084)	(-0.008)	
Long/Short (vw)	1.787	-0.236	-0.240	-0.484	-0.033	0.026
	(3.289)	(-1.708)	(-1.328)	(-2.390)	(-0.190)	

Table 7: **Quarterly EPS Forecast Errors**
This table shows the forecast error normalized by the stock price according to our two measures, Downstream Outperformance, here in quintiles and vertical integration, grouped in quartiles. We define the forecast error as the difference between the actual EPS and a constructed recent EPS median forcast. To avoid stale forecasts, we collect from the IBES details file all forecasts that were issued in the second half of the fiscal quarter or, alternatively, after the fiscal quarter end. Furthermore, we require that the analyst had issued already forecasts in the preceeding calendar year. To make sure that the analyst actively followed the company we restrict all collected forecasts to those for which we have a preceeding forecast for the same company and fiscal quarter from the same analysts. We control for obvious data errors by eliminating forecasts which differ by more than 10$ from the actual EPS. A positive value implies that the acutal EPS is higher than the median analyst forcast and the market is 'positively' surprised. BACKWARD contains firms which we consider as backward integrated, whereas FORWARD has tentatively forward integrated firms. NOVERT contains the firms for which we have a measure $VERT$ unequal to zero, but are not in one of the other two groups. Second, we create quintiles of the downstream outperformance. The t-statistics reported in column eight correspond to the difference in mean forecasts errors between fifth and first DSOP quintlies and are based on standard errors clustered by stock and year.

	Downstream Outperformance						
	Q 1	Q 2	Q 3	Q 4	Q 5	(5-1)	t-value
FORWARD+BACKWARD	-0.23	-0.06	0.02	-0.06	-0.02	0.21	2.23
NOVERT	-0.05	-0.05	-0.06	0.01	-0.03	0.02	0.38
FORWARD	-0.25	0.01	-0.14	-0.04	-0.06	0.19	1.05
BACKWARD	-0.22	-0.12	0.14	-0.08	-0.00	0.22	2.07

Table 8: **The Number of Firms Traded By Month** This table details the number of firms entering the monthly trading strategy of Table 6 for each month in the sample period.

Month	Long	Short	Month	Long	Short	Month	Long	Short
09-1984	1	1	02-1989	6	6	12-1992	3	3
10-1984	15	14	03-1989	4	3	01-1993	21	21
11-1984	3	2	04-1989	13	13	02-1993	15	15
12-1984	1	1	05-1989	2	2	03-1993	8	7
01-1985	11	11	06-1989	3	3	04-1993	31	30
02-1985	6	5	07-1989	12	12	05-1993	10	10
03-1985	1	1	08-1989	5	4	06-1993	3	2
04-1985	19	19	09-1989	2	1	07-1993	34	33
06-1985	1	1	10-1989	15	15	08-1993	10	9
07-1985	16	16	11-1989	4	3	09-1993	3	3
08-1985	3	3	12-1989	3	2	10-1993	37	37
10-1985	17	16	01-1990	7	7	11-1993	7	6
11-1985	3	2	02-1990	7	6	12-1993	4	3
04-1986	14	13	03-1990	3	2	01-1994	24	24
05-1986	2	1	04-1990	15	15	02-1994	19	19
06-1986	2	2	05-1990	3	2	03-1994	9	8
07-1986	13	12	06-1990	2	2	04-1994	37	36
08-1986	4	4	07-1990	14	13	05-1994	9	9
09-1986	1	1	08-1990	4	3	06-1994	5	5
10-1986	15	14	09-1990	1	1	07-1994	38	37
11-1986	3	2	10-1990	16	15	08-1994	10	10
12-1986	2	2	11-1990	2	2	09-1994	4	4
01-1987	11	10	12-1990	2	2	10-1994	37	37
02-1987	4	4	01-1991	10	10	11-1994	9	9
03-1987	2	2	02-1991	6	6	12-1994	2	2
04-1987	17	16	03-1991	4	3	01-1995	27	27
05-1987	1	1	04-1991	15	14	02-1995	19	19
06-1987	2	2	05-1991	2	1	03-1995	8	7
07-1987	16	15	06-1991	2	1	04-1995	38	37
08-1987	3	3	07-1991	16	16	05-1995	12	12
09-1987	2	2	08-1991	5	4	06-1995	3	3
10-1987	15	15	09-1991	1	1	07-1995	36	36
11-1987	2	2	10-1991	16	16	08-1995	12	11
12-1987	2	2	11-1991	2	2	09-1995	4	3
01-1988	11	11	12-1991	2	1	10-1995	37	37
02-1988	7	7	01-1992	14	14	11-1995	13	13
03-1988	2	2	02-1992	5	5	12-1995	3	2
04-1988	16	16	03-1992	3	2	01-1996	26	25
06-1988	2	1	04-1992	16	16	02-1996	20	20
07-1988	14	13	05-1992	4	3	03-1996	10	9
08-1988	4	4	06-1992	1	1	04-1996	41	41
09-1988	2	2	07-1992	15	15	05-1996	12	12
10-1988	15	15	08-1992	4	4	06-1996	5	4
11-1988	4	3	09-1992	2	1	07-1996	43	43
12-1988	3	2	10-1992	14	14	08-1996	11	11
01-1989	12	11	11-1992	4	3	09-1996	5	5

...Table 8 continued. The Number of Firms Traded By Month.

Month	Long	Short	Month	Long	Short	Month	Long	Short
10-1996	45	44	08-2000	23	23	06-2004	5	5
11-1996	10	10	09-2000	8	8	07-2004	55	50
12-1996	3	3	10-2000	53	53	08-2004	20	20
01-1997	29	29	11-2000	17	16	09-2004	7	6
02-1997	23	23	12-2000	9	9	10-2004	50	50
03-1997	10	10	01-2001	44	43	11-2004	21	20
04-1997	41	41	02-2001	34	33	12-2004	5	5
05-1997	12	12	03-2001	8	8	01-2005	32	31
06-1997	5	5	04-2001	66	66	02-2005	34	34
07-1997	42	42	05-2001	17	17	03-2005	14	14
08-1997	13	12	06-2001	9	9	04-2005	45	42
09-1997	5	4	07-2001	67	67	05-2005	27	27
10-1997	44	44	08-2001	26	26	06-2005	8	7
11-1997	11	11	09-2001	7	7	07-2005	47	46
12-1997	3	2	10-2001	72	71	08-2005	27	26
01-1998	30	29	11-2001	18	17	09-2005	5	4
02-1998	26	26	12-2001	7	6	10-2005	41	41
03-1998	3	3	01-2002	47	46	11-2005	30	29
04-1998	40	40	02-2002	35	34	12-2005	5	4
05-1998	11	11	03-2002	8	7	01-2006	28	28
06-1998	4	4	04-2002	63	62	02-2006	35	34
07-1998	38	38	05-2002	20	19	03-2006	15	14
08-1998	11	11	06-2002	7	7	04-2006	40	40
09-1998	4	3	07-2002	68	68	05-2006	37	36
10-1998	36	36	08-2002	19	19	06-2006	6	5
11-1998	12	12	09-2002	8	8	07-2006	43	43
12-1998	3	3	10-2002	69	69	08-2006	33	32
01-1999	25	25	11-2002	18	17	09-2006	8	7
02-1999	24	24	12-2002	8	7	10-2006	44	44
03-1999	7	6	01-2003	37	35	11-2006	34	34
04-1999	64	63	02-2003	33	33	12-2006	5	4
05-1999	19	19	03-2003	9	9	01-2007	29	28
06-1999	8	8	04-2003	46	46	02-2007	42	42
07-1999	64	61	05-2003	19	18	03-2007	16	15
08-1999	24	24	06-2003	7	6	04-2007	41	40
09-1999	9	9	07-2003	48	48	05-2007	33	33
10-1999	67	60	08-2003	18	17	06-2007	6	5
11-1999	22	22	09-2003	5	5	07-2007	42	42
12-1999	8	7	10-2003	54	45	08-2007	30	29
01-2000	41	36	11-2003	18	18	09-2007	5	5
02-2000	47	47	12-2003	6	5	10-2007	38	38
03-2000	10	9	01-2004	34	34	11-2007	25	25
04-2000	63	60	02-2004	30	29	12-2007	4	4
05-2000	27	26	03-2004	12	11			
06-2000	9	8	04-2004	53	53			
07-2000	60	60	05-2004	17	17			