Economic Links and Predictable Returns*

Lauren Cohen
Yale School of Management

Andrea Frazzini
University of Chicago
Graduate School of Business and NBER

This draft: May 23, 2007
First draft: January 30, 2006

* We would like to thank Nick Barberis, Effi Benmelech, Judy Chevalier, Kent Daniel, Doug Diamond, Gene Fama, Will Goetzmann, Ravi Jagannathan, Anil Kashyap, Josef Lakonishok, Owen Lamont, Jonathan Lewellen, Toby Moskowitz, Lubos Pastor, Lasse Pedersen, Monika Piazzesi, Joseph Piotroski, Doug Skinner, Matt Spiegel, Robert Stambaugh, Amir Sufi, Josh Rauh, Jake Thomas, Tuomo Vuolteenaho, Ivo Welch, Wei Xiong, an anonymous referee and seminar participants at the NBER, Barclays Global Investors, the BSI Gamma Foundation, The Chicago Quantitative Alliance, the University of Chicago, American Finance Association, European Finance Association, Goldman Sachs Asset Management, Lehman Brothers, London Business School, NYU, Harvard Business School, MIT, Yale University, AQR Capital Management, Prudential Equity Conference, and UC Davis Conference on Financial Markets Research, for helpful comments. We also thank Wooyun Nam, Vladimir Vladimirov, and Jeri Xu for excellent research assistance, Husayn Shahrur and Jayant Kale for providing us with some of the customer-supplier data, the Chicago Quantitative Alliance and the BSI Gamma foundation for financial support. All errors are our own.

ABSTRACT

This paper finds evidence of return predictability across economically linked firms. We test the hypothesis that in the presence of investors subject to attention constraints, stock prices do not promptly incorporate news about economically related firms, generating return predictability across assets. We use a dataset of firms' principal customers to identify a set of economically related firms, and show that stock prices do not incorporate news involving related firms, generating predictable subsequent price moves. A long/short equity strategy based on this effect yields monthly alphas of over 150 basis points.

JEL Classification: G10, G11, G14

Key words: Economic links, customers, suppliers, inattention

Firms do not exist as independent entities, but are linked to each other through many types of relationships. Some of these links are clear and contractual, while others are implicit and less transparent. We use the former of these, clear economic links, as an instrument to test investor inattention. Specifically, we focus on well defined customer-supplier links between firms. In these cases, partner firms are stakeholders in each others' operations. Thus, any shock to one firm has a resulting effect on its linked partner. We examine how shocks to one firm translate into shocks to the linked firm in both real quantities (i.e. profits) and stock prices. If investors take into account the ex-ante publicly available[1] and often longstanding customer-supplier links, prices of the partner firm will adjust when news about its linked firm is released into the market. If, in contrast, investors ignore publicly available links, stock prices of related firms will have a predictable lag in updating to new information about firms' trading partners. Thus, the asset pricing implications of investors with limited attention is that price movements across related firms are predictable: prices will adjust with a lag to shocks of related firms, inducing predictable returns.

There are two conditions that need to be met to test for investor limited attention. First, any information thought to be overlooked by investors needs to be available to the investing public before prices evolve. Second, the information needs to be, in fact, salient information that investors should be reasonably expected to gather. The latter of the two conditions is clearly less objective and more difficult to satisfy. We believe that customer-supplier links do satisfy both requirements, and provide a natural setting for testing investor limited attention.

First, information on the customer-supplier link is publicly available in that firms are required to disclose information about operating segments in their financial statements issued to the shareholder. Regulation SFAS No. 131 requires firms to report the identity of customers representing more than 10% of the total sales in interim financial reports issued to shareholders. In our linked sample, the average customer accounts for 20 percent of the sales of the supplier firm. Therefore, customers represent substantive stakeholders in the supplier firms. Furthermore, in some cases, the

[1] The customer-supplier links we examine in the paper are those sufficiently material as to be required by SFAS 131 to be reported in public financial statements. We discuss the reporting standard in Section II.

customer-supplier links are longstanding relationships with well defined contractual ties. Second, and more importantly, as we do examine material customer-supplier links, the link is in fact salient information when forming expectations about future cash flows, and so prices. Not only is it intuitive that investors should take this relationship into account, we provide evidence that real activities of firms depend on the customer-supplier link.

To test for return predictability, we group stocks into different classes for which news about linked firms has been released into the market, and construct a long/short equity strategy. The central prediction is that returns of linked firms should forecast future returns of the partner firms' portfolios.

To better understand our approach, consider the customer-supplier link of Coastcast and Callaway, which is shown in accompanying Figure 1. In 2001, Coastcast Corporation was a leading manufacturer of golf club heads. Since 1993 Coastcast's major customer had been Callaway Golf Corporation, a retail company specialized in golf equipment[2]. As of 2001, Callaway accounted for 50% of Coastcast's total sales. On June 7, Callaway was downgraded by one of the analysts covering it. In a press release on the next day Callaway lowered second quarter revenue projections to $250 million, down from a previous revenue of $300 million. The announcement brought the expected second quarter earnings per share (EPS) down to between 35 cents and 38 cents, about half of the current mean forecast of 70 cents a share. By market close on June 8, Callaway shares were down by $6.23 to close at $15.03, a 30% drop since June 6. In the following week the fraction of analysts issuing "buy" recommendation dropped from 77% to 50%. Going forward, nearly two months later, when Callaway announced earnings on July 25, they hit the revised mean analyst estimate exactly with 36 cents per share.

Surprisingly, the negative news in early June about Callaway future earnings did not impact at all Coastcast's share price. Coastcast's stock price was unaffected, despite the fact that the single customer accounting for half of Coastcast's total sales dropped 30% of market value in two days. Both EPS forecast ($2) and stock recommendations (100% buy) were not revised. Furthermore, a Factiva search of newswires and financial

[2] Both firms traded on the NYSE and had analyst coverage.

publication returned no news mentions for Coastcast at all during the two-month period subsequent to Callaway's announcement. Coastcast announced EPS at -4 cents on July 19, and Coastcast experienced negative returns over the subsequent two months.

[Insert figure 1 here]

In this example, we were unable to find any salient news release about Coastcast other than the announcement of a drop in revenue of its major customer. However, it was not until two months later that the price of Coastcast adjusted to the new information. A strategy that would have shorted Coastcast on news of Callaway's slowing demand would have generated a return of 20% over the subsequent two months.

The above example represents in fact a much more systematic pattern across the universe of US common stocks: consistent with investors' inattention to company links, there are significantly predictable returns across customer-supplier linked firms. Our main result is that the monthly strategy of buying firms whose customers had the most positive returns (highest quintile) in the previous month, and selling short firms whose customers had the most negative returns (lowest quintile), yields abnormal returns of 1.55% per month, or an annualized return of 18.6 percent per year. We refer to this return predictability as "customer momentum". Moreover, returns to the customer momentum strategy have little or no exposure to the standard traded risk factors, including the firm's own momentum in stock returns.

We test for a number of alternative explanations of the customer momentum result. It could be that unrelated to investor limited attention of the customer-supplier link, the effect could be driven by the supplier's own past returns, which may be contemporaneously correlated with the customer's. In this case customer return is simply a noisy proxy for own past return of the supplier. Thus, we control for the firm's own past returns, and find that controlling for own firm momentum does not affect the magnitude or significance of the customer momentum result. Alternatively, the result could be driven by industry momentum (Moskowitz and Grinblatt (1999)) or by a lead-lag relationship (Lo and MacKinlay (1990), Hou and Moskowitz (2005) and Hou (2006)). Explicitly controlling for these effects does not have a significant impact on the magnitude or the significance of the customer momentum result. Finally, a recent paper by Menzly and Ozbas (2006) uses upstream and downstream definitions of industries to define cross-industry momentum. We find that controlling for cross-industry momentum also does not affect the customer momentum result.

If limited investor attention is driving this return predictability result from the customer-supplier link, it should be true that varying inattention varies the magnitude and significance of the result. We use mutual funds joint holdings of the customer and supplier firm to identify a subset of firms where investors are, a priori, more likely to collect information on both customer and supplier, and so be attentive to the customer-supplier link. For all mutual funds that own the supplier firm, we classify the percent that own both customer and supplier (common), and the percent that own only the supplier (non common). We show that return predictability is indeed significantly more (less) severe where inattention constraints are more (less) likely to be binding. Further, we show that common mutual fund managers are significantly more likely to trade the supplier on linked customer firm shocks, whereas non common managers trade the supplier only with a significant (1 quarter) lag to the same customer shocks.

Finally, we turn to measures of real activity and show that the customer-supplier link does matter for the correlation of real activities between the two firms. We do this by exploiting time series variation in the same firms being linked and not linked over the sample. We look at real activity of linked firms and find that during years when the firms are linked, both sales and operating income are significantly more correlated than during non-linked years. We then also show that when two given firms are linked, customer shocks today have significant predictability over future supplier real activities, while when they are not linked, there is no predictable relationship. Also, the sensitivity of suppliers' future returns to customer shocks today doubles when customer-supplier are linked as opposed to not linked.

The remainder of the paper is organized as follows. Section I provides a brief background and literature review. Section II describes the data, while Section III details the predictions of the limited investor attention hypothesis. Section IV establishes the main customer momentum result. Section V provides robustness checks and considers alternative explanations. Section VI explores variation in inattention and customer momentum. Section VII examines the real effects of the customer-supplier link. Section VIII concludes.

I. Background and literature review

There is a large body of literature in psychology regarding individuals' ability to allocate attention between tasks. This literature suggests that individuals have a difficult time processing many tasks at once[3]. Attention is a scarce cognitive resource and attention to one task necessarily requires a substitution of cognitive resources from other tasks (Kahneman (1973)). Given the vast amount of information available and their limited cognitive capacity, investors may choose to select only a few sources of salient information.

One of the first theoretical approaches to segmented markets and investor inattention is Merton's (1987) model. In his model, investors obtain information (and trade) on a small number of stocks. Stocks with fewer traders sell at a discount stemming from the inability to share risks. Hong and Stein (1999) develop a model with multiple investor types, in which information diffuses slowly across markets and agents do not extract information from prices, generating return predictability. Hirshleifer and Teoh (2003) and Peng and Xiong (2006) also model investor inattention and derive empirical implications for security prices. Hirshleifer and Teoh (2003) focus on the presentation of firm information in accounting reports and the effect on prices and misvaluation. Peng and Xiong (2006) concentrate on investors' learning behavior given limited attention.

An empirical literature is also beginning to build regarding investor limited attention. Huberman and Regev (2001) study investor inattention to salient news about a firm. In their study, a firm's stock price soars on re-release of information in the *New York Times* that had been published in *Nature* five months earlier. Turning to return predictability, Ramnath (2002) examines how earnings surprises of firms within in the same industry are correlated. He finds that the first earnings surprise within an industry has information for both the earnings surprises of firms within the industry, and of returns of other firms within the industry. Hou and Moskowitz (2005) study measures of

[3] For a summary of the literature, see Pashler and Johnston (1998).

firm price delay and find that these measures help to explain (or cause variation) in many return factors and anomalies. Furthermore, they find that the measure of firm price delay seems related to a number of potential proxies for investor recognition. Hou (2006) finds evidence that such lead-lag effects are predominantly an intra-industry phenomenon: returns on large firms lead returns on small firms within the same industry.

Barber and Odean (2006) use a number of proxies for attention grabbing events (ex. news and extreme past returns), and find that both positive and negative events result in individual investor buying of securities (with an asymmetry on selling behavior). Further, they find that institutions do not exhibit this same attention based trading behavior. DellaVigna and Pollet (2007) use demographic information to provide evidence that demographic shifts can be used to predict future stock returns. They interpret this as the market not fully taking into account the information contained in demographic shifts. DellaVigna and Pollet (2006) then look at the identification of weekends as generating a distraction to investor attention. They find that significantly worse news is released by firms on Friday earnings announcements, and that these Friday announcements generate a larger post earnings announcement drift. Hou, Peng, and Xiong (2006) use trading volume as a proxy for attention, and show that variation in this proxy can cause significant variation in both momentum and post earnings announcement drift returns. Bartov and Bodnar (1994) examine the interaction of the foreign exchange and equity markets and find that lagged movements in the dollar exchange rate predict future abnormal returns and future earnings surprises. Hong, Lim, and Stein (2000), look at price momentum to test the model of Hong and Stein (1999) and find that information, and especially negative information, diffuses gradually into prices.

Two recent papers closely related to ours are Hong, Tourus, and Valkanov (2005) and Menzly and Ozbas (2006). Hong, Tourus, and Valkanov (2005) look at investor inattention in ignoring lagged industry returns to predict total equity market returns. They find that certain industries do have predictive power over future market returns, with the same holding true in international markets. Menzly and Ozbas (2006) use upstream and downstream definitions of industries and present evidence of cross-industry momentum. In addition, Menzly and Ozbas (2006) find results for a limited sample in support of ours: that individual customer returns do predict future supplier's returns. While both of these papers provide valuable evidence on slow diffusion of information, our approach is different. We do not restrict the analysis to specific industries or specific links within or across industries. On the other hand we focus on what we believe from the investors' standpoint may be the more intuitive links of customer and supplier. We do not impose any structure on the relation, but simply follow the evolution of customer/supplier firm-specific relations over time. Thus, our data allows us to test for return predictability of individual stocks stemming from company-specific linkages when firm-specific information is released into the market and generates large price movements. Not surprisingly, our results are robust to controls for both intra and inter industry effects.

II. Customer data

The data is obtained from several sources. Regulation SFAS No. 131 requires firms to report selected information about operating segments in interim financial reports issued to shareholders. In particular, firms are required to disclose certain financial information for any industry segment that comprised more than 10% of consolidated yearly sales, assets or profits, and the identity of any customer representing more than 10% of the total reported sales[4]. Our sample consists of all firms listed in the CRSP/Compustat database with non missing value of book equity (BE) and market equity (ME) at the fiscal-year end, for which we can identify the customer as another traded CRSP/Compustat firm. We focus the analysis on common stocks only.[5]

We extract the identity of the firm's principal customers from the Compustat segment files[6]. Our customer data cover the period between 1980 and 2004. For each firm we determine whether the customer is another company listed on the CRSP/ Compustat tape and we assign it the corresponding CRSP permno number. Prior to

[4] Prior to 1997, Regulation SFAS No. 14 governed segment disclosure. SFAS No. 131, issued by the FASB in June 1997, was effective for fiscal years beginning after December 15, 1997.

[5] CRSP share codes 10 and 11.

[6] We would like to Husayn Shahrur and Jayant Kale, and the research staff at WRDS for making some of the customer data available to us.

1998, most firms' customers are listed as an abbreviation of the customer name, which may vary across firms or over time. For these firms, we use a phonetic string matching algorithm to generate a list of potential matches to the customer name, and subsequently we hand-match the customer to the corresponding permno number by inspecting the firm's name, segments and industry information[7]. We are deliberately conservative in assigning customer names and firm identifiers to make sure that customers are matched to the appropriate stock returns and financial information. Customers for which we could not identify a unique match are excluded from the sample.

To ensure that the firm-customer relations are known before the returns they are used to explain, we impose a six month gap between fiscal year end dates and stocks returns. This mimics the standard gap imposed to match accounting variables to subsequent price and return data[8]. The final sample includes 30,622 distinct firm-year-relationships, representing a total of 11,484 unique supplier–customer relationships between 1980 and 2004.

Table I shows summary statistics for our sample. In Panel A we report the coverage of the firms in our data as a fraction of the universe of CRSP common stocks. One important feature of the sample of stocks we analyze is the relative size between firms and their principal customers. The size distribution of firms in our sample closely mimics the size distribution of the CRSP universe. On the other hand, the sample of firm's principal customers is tilted toward large cap securities: the average customer size is above the 90th size percentile of CRSP firms. This difference partially reflects the data generating process. Firms are required to disclose the identity of any customer representing more than 10% of the total reported sales, thus we are more likely to identify larger firms as customers, since larger firms are more likely to be above the 10% sale cutoff.

[Insert table I here]

[7] We use a "soundex" algorithm to generate a list of potential matches.
[8] See, for example Fama ands French (1993).

On average the universe of stock in this study comprises 50.6% of the total market capitalization and 20.25% of the total number of common stocks traded on the NYSE, AMEX and NASDAQ. The last row of Panel A shows that on average 78% of firm-customer relations are between firms in different industries[9]. This is not surprising given that inputs provided by the firms in our sample are often quite different from the final outputs sold by their principal customers. Thus, the stock return predictability we analyze is mostly related to assets in different industries as opposed to securities within the same industry.

III. Limited attention hypothesis and underreaction

In this section we describe the main hypothesis and design a related investment rule to construct the test portfolios. We conjecture that in the presence of investors that are subject to attention constraints, stock prices do not promptly incorporate news about related firms, and thereby generate price drift across securities.

HYPOTHESIS LA (LIMITED ATTENTION): *Stock prices underreact to firm-specific information that induces changes in valuation of related firms, generating return predictability across assets. Stock prices underreact to negative news involving related firms, and in turn generate negative subsequent price drift. Similarly, stock prices underreact to positive news involving related firms, and in turn generate positive subsequent price drift.*

In a world where investors have limited ability to collect and gather information, and market participants are unable to perform the rational expectations exercise to extract information from prices, returns across securities are predictable. News travels slowly across assets as investors with limited attention overlook the impact of specific information on economically related firms. These investors tend to hamper the transmission of information, generating return predictability across related assets.

Hypothesis LA implies that a long-short portfolio, in which a long position in stocks whose related firms recently experienced good news is offset by a short position in

[9] We assign stocks to 48 industries based on their SIC code. The industry definitions are from Ken French's website.

stocks whose related firms experienced bad news, should yield positive subsequent returns. We refer to this strategy as the *customer momentum* portfolio. The customer momentum portfolio is the main test portfolio in our analysis.

Since some firms in our sample have multiple principal customers over many periods, we construct an equally weighted portfolio of the corresponding customers using the last available supplier-customer link. We rebalance these portfolios every calendar month. Hereafter, we refer to the monthly return of this portfolio as the *customer return*[10]. In our base specification, we use the monthly customer return as a proxy for news about customers. We believe that a return-driven news sort is appropriate because it closely mimics the underreaction hypothesis at hand.

To test for return predictability, we examine monthly returns on calendar time portfolios formed by sorting stocks on their lagged customer return. At the beginning of calendar month t, we rank stocks in ascending order based on the customer returns in month $t-1$ and we assign them to one of five quintile portfolios. All stocks are value (equally) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights.

The time series of returns of these portfolios tracks the calendar month performance of a portfolio strategy that is based entirely on observables (lagged customer returns). This investment rule should earn zero abnormal returns in an efficient market. We compute abnormal returns from a time-series regression of the portfolio excess returns on traded factors in calendar time.[11] Positive abnormal returns following positive customer returns indicate the presence of customer momentum, consistent with underreaction or a sluggish stock price response to news about related firms. The opposite is true for negative news. Under the Hypothesis LA, controlling for other characteristics associated with expected returns, bad customer news stocks

[10] Using different weighting schemes to compute customer returns does not affect the results. We replicated all our results using customer returns computed by setting weights equal to the percent of total sales going to each customer. For most of the paper, we chose to focus on equally weighted customer returns to maximize the number of firms in our sample, since unfortunately the dollar amount of total sales going to each customer is missing in about 19% of firm-year observations of our linked data.

[11] We obtain the monthly factors and the risk-free rate from Ken French's website:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html consistently underperform good customer news stocks, generating positive returns of our zero cost long/short investment rule.

Finally, note that since we are interested in testing whether investors in fact do take into account the customer-supplier link when forming and updating prices, in principle there is no reason to restrict the analysis to a customer momentum strategy. The current financial regulation, though, requires firms to report major customers (and not major suppliers). Given the presence of the 10% cutoff, our sample has more information about customers who are major stakeholders, and not the reverse. Thus, our main tests are in the direction of suppliers' stock price response to customers' shocks[12].

IV. Results

Table II reports correlations between the variables we use to group stocks into portfolios. The correlations are based on monthly observations pooled across stocks. Not surprisingly, returns and customer returns are associated with each other. Customer returns tend to be uncorrelated with firm size, defined as the logarithm of market capitalization at the end of the previous month, market to book ratios (market value of equity divided by Compustat book value of equity) and the stock's return over the previous calendar year.

[Insert table II here]

There is a distinctive characteristic of the data that should be emphasized. A caveat that arises when sorting stocks using customer returns is that, given the large average size of the customers in our sample, it is likely for customer returns to be highly correlated with the return of the corresponding industry. Ideally, we would like our test portfolios to contain stocks with similar industry exposure (both to the underlying industry and to the corresponding customer industry) but a large spread in customer returns. In Section V, we specifically address this issue by calculating abnormal returns of our test portfolios after hedging out inter and intra industry exposure.

[12] In unreported results, we construct measures of important supplier stakeholders and found evidence of predictability from supplier to customer stock returns. These results are available upon request.

Table III shows the basic results of this paper. We report returns in month *t* of portfolios formed by sorting on customer returns in month *t-1*. The rightmost column shows the returns of a zero cost portfolio that holds the top 20 percent high customer return stocks and sells short the bottom 20 percent low customer return stocks. To be included in the portfolio, a firm must have a non missing customer return and non missing stock price at the end of the previous month. Also, we set a minimum liquidity threshold by not allowing trading in stocks with a closing price at the end of the previous month below $5[13]. This ensures that portfolio returns are not driven by micro-capitalization illiquid securities.

Separating stocks according to the lagged return of related firms induces large differences in subsequent returns. Looking at the difference between high customer return and low customer return stocks, it is striking that high (low) customer return today predicts high (low) subsequent stock returns of a related firm. The customer momentum strategy that is long the top 20% good customer news stocks and short the bottom 20% bad customer news stocks delivers Fama and French (1993) abnormal returns of 1.45% per month (t-statistic = 3.61), approximately 18.4% per year. Adjusting returns for the stock's own price momentum by augmenting the factor model with Carhart's (1997) momentum factor has a negligible effect on the results. Subsequent to portfolio formation, the baseline long short portfolio earns abnormal returns of 1.37% per month (t-statistic = 3.12). Last, we adjust returns using a 5-factor model by adding the traded liquidity factor by Pastor and Stambaugh (2003)[14]. The liquidity adjustment has little effect on the result: subsequent to portfolio formation, the baseline zero cost portfolio earns abnormal returns of 1.24% per month (t-statistic = 2.99). The results show that even after controlling for past returns or a reversal measure of liquidity, high (low) customer momentum stocks earn high (low) subsequent (risk-

[13] We have run the tests in the paper also relaxing this $5 cut-off, and all results in the paper are robust to this. These results are available upon request.

[14] The traded liquidity factor is obtained by sorting the CRSP monthly stocks file data into ten portfolios based on their sensitivity to the liquidity innovation series, as described in Pastor and Stambaugh (2003). The traded factor is the (value weighted) return of a zero cost portfolio that is long the highest liquidity beta portfolio and short the lowest liquidity beta portfolio.

adjusted) returns.[15] We return to this issue in Section V where we use a regression approach to allow for a number of control variables.

The alphas rise monotonically across the quintile portfolios as the customer return goes from low (negative) in portfolio #1 to high (positive) in portfolio #5. Although abnormal returns are large and significant for both legs of the long/short strategy, customer momentum returns are asymmetric: the returns of the long short portfolio are largely driven by slow diffusion of negative news. This pattern is consistent with market frictions (such as short sale constraints) exacerbating the delayed response of stock prices to new information when bad news arrives[16]. Using equal weights rather than value weights delivers similar results: the baseline customer momentum portfolio earns a monthly alpha of 1.3% (t-statistic = 4.93).

[Insert table III here]

Figure 2 illustrates the result by reporting how customer returns predict individual stock returns at different horizons. We show the cumulative average returns in month $t+k$ on the long/short customer momentum portfolios formed on customer returns in month t. We also plot the cumulative abnormal return of the customer portfolio (the sorting variable). To allow for comparisons, we show returns of the customer portfolio times the total fraction of the supplier firm's sales accounted for by the principal customers. Figure 2 shows that supplier stock prices react to information that causes large swings in the stock price of their principal customers. Looking at the long/short portfolio, supplier stock prices rise by 3.9% in month zero, where the (sales-weighted) customer portfolio jumps by 7.8%. Nevertheless, stock prices drift in the same direction subsequent to the initial price response. The customer momentum portfolio earns a cumulative 4.73 percent over the subsequent year. The predictable positive returns persist for about a year and then fade away.

---

[15] In addition, none of the 5-factor loadings are significant for the long/short customer momentum portfolio.

[16] Note that the abnormal returns are negative for most of the portfolios. This is due to the fact that during the sample period the average supplier has underperformed the market. The 3-factor monthly alpha of an equally weighted portfolio of all suppliers in our sample is -41bp, probably due to the fact that US suppliers have been continuously squeezed by international competition (we thank Tuomo Vuolteenaho for suggesting this interpretation).

[Insert figure 2 here]

In Table IV we explore the relation between the customer returns, the initial stocks price reaction of related firms, and the subsequent price drift on both customer and supplier. We compute customer returns using weights equal to the percent of total sales going to each customer, and form calendar time portfolios as before. In Panel A we report the average cumulative returns on a long/short portfolio formed on the firm's (sales-weighted) customer return in month *t*. CRET is the (sales-weighted) customer return in month *t*, CCAR is the customer cumulative returns over the subsequent six months. RET is the supplier stock return in month *t*. CAR is its cumulative return over the subsequent six months. In Panel B we report the "UnderReaction" coefficients (URC) for both the customer and the suppliers. URC is a measure of the initial price response to a given shock as a fraction of the subsequent abnormal return. URC is defined as the fraction of total return from month *t* to month *t+6* that occurs in month *t*, URC = RET / (RET + CAR), and is designed to proxy for the amount of underreaction of a stock. If the market efficiently incorporates new information, this fraction should on average be equal to one. Values of URC less than one indicate the presence of underreaction or a sluggish stock price response to news about customers. Conversely, values of URC greater than one indicate the presence of overreaction to the initial news content embedded in the customer return[17].

[Insert table IV here]

The results in Table IV show that on average stock prices underreact to information about related customers by roughly 40%. That is, when customers experience large returns in a given month *t*, the stock price of a related supplier reacts by covering about 60% of the initial price gap in month *t*, and it subsequently closes the remaining 40% over the next six months. This can also be seen in the significant positive CAR of the supplier portfolio of 2.8 % (t-statistic = 3.74) following the initial price movement of the customer. Note from Panel B that the URC for customers is 0.94

[17] We thank Owen Lamont for suggesting this measure to us.

and not statistically different from one. Another way to see this, from Panel A of Table IV, is that customers do not have a significant CCAR following the initial price jump. That is, while information that generates large price movements for the customer is quickly impounded into the customer's stock price, only a fraction of the initial price response (60%) spills over to supplier's stock price, generating the profitability of the customer momentum portfolio. Looking at larger firms versus smaller firms (defined as firms below or above the median market capitalization of all CRSP stocks that month) reveals that the underreaction coefficients tend to be negatively related to size. Larger firms cover 69% of the abnormal drift in the initial month, closing the remaining 31% gap in the subsequent six months. Smaller firms cover only 35% of the gap in the initial month, closing the remaining 65% in the subsequent six months. We return to this issue in Section V. Although the customer momentum total abnormal return is roughly the same in large and small cap securities, prices tend to converge faster for large cap stocks.

The results in Tables III and IV, and Figure 2 support Hypothesis LA: news travels slowly across stocks that are economically related, generating large subsequent returns on a customer momentum portfolio. When positive news hits a portfolio of a firm's customers, it generates a large positive subsequent drift, as initially the firm's stock price adjusts only partially. Conversely, when a portfolio of customers experiences large negative returns in a given month, stock prices have (predictable) negative subsequent returns. This effect generates the profitability of customer momentum portfolio strategies. These findings are consistent with firms adjusting only gradually to news about economically linked firms.

V. Robustness tests

A. Nonsynchronous trading, liquidity, characteristics, and size

Although the results are consistent with the LA hypothesis, there are a number of other plausible explanations of the data. Table V shows results for a series of robustness tests.

A number of papers find that larger firms, or firms with higher levels of analyst coverage, institutional ownership, and trading volume, lead smaller firms or firms with lower levels of analyst coverage, institutional ownership, and trading volume[18]. Given the fact the average customer tends to be much larger than the average supplier (Table I), the customer momentum results could be a manifestation of the lead-lag effect among firms of different size, analyst coverage, institutional ownership, and trading volume. To ensure that lead-lag effects are not driving the predictability from customer to suppliers, in Panel A of Table V we show value weighted customer momentum returns where we drop all links from the portfolios where, at portfolio formation, customer firms are larger than supplier firms, where customer firms have higher turnover, where customer firms have a higher number of analysts providing earnings estimates and finally where customer firms have higher institutional ownership[19]. These filters reduce the sample considerably, given that SFAS 131 requires firms to report customers accounting for at least 10% of reported sales. Results in Panel A of Table V show that the customer momentum predictability is largely unaffected by this adjustment, indicating that lead lag effects are unlikely to account for the results. After restricting investments to firms that are large than their customers, the average monthly 5-factor alpha across all 4 specifications is around 1.37% per month and, although portfolios are much less diversified given the limited sample, we can safely reject the null hypothesis of no predictability on each of the four specifications. We further return to the issue of lead-lag effects in the subsection below, where we use cross sectional regressions to allow for a richer set of controls

Panel B of Table V presents additional robustness tests. We show average monthly returns of the long/short customer momentum portfolio. In Columns 1 to 4 we report the return of portfolios sorted on lagged 1-month customer return. Nonsynchronous trading can generate positive autocorrelation across stocks.[20] In the analysis, we use monthly data and exclude low priced stocks when constricting the test assets, hence; nonsynchronous trading is unlikely to be driving the results. Confirming

[18] Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), and Chordia and Swaminathan (2000), Hou and Moskowitz (2005) and Hou (2006).

[19] We are grateful to the referee for suggesting these tests. We define turnover TURN as the average daily turnover (volume divided by shares outstanding) in the prior year. Analyst coverage NUMEST is the number of analysts providing forecasts of earnings per share for the current fiscal year. Analysts forecasts are from I/B/E/S. Institutional ownership IO is defined as the total number shares owned by intuitions reporting common stocks holdings (13f) to the SEC as of the last quarter-end divided by the number of shares outstanding. Institutional holdings are from Thomson Financial.

[20] Lo and MacKinlay (1990).

this intuition, Table V shows that skipping a week between portfolio formation and investment has little effect on the return of the customer momentum portfolio. Also, although we exclude low priced stocks when constricting the test assets, it is plausible that some illiquid stocks are not captured by this rough filter. Furthermore, there is the possibility some stocks don't trade for weeks, thus generating an apparent lagged reaction to news, not captured by simply skipping a week between portfolio formation and investment. To control for liquidity effects, we compute the test asset by only including stocks with strictly positive volume every trading day over the previous 12 months. Results in Table V shows this adjustment has little effect on the return of the customer momentum portfolio. Given the evidence on 5-factor alphas in Table III and the results of Table V, we conclude that liquidity is unlikely to be driving the customer momentum result.

[Insert table V here]

Daniel and Titman (1997, 1998) suggest that characteristics can be better predictors of future returns than factor loadings. Following Daniel, Grinblatt, Titman, and Wermers (1997), we subtract from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles (a total of 125 matching portfolios)[21]. We industry-adjust returns in a similar fashion using the 48 industry matched portfolios[22]. The results in Table VI show that firms whose customers experienced good (bad) news out (under) perform their corresponding characteristic portfolios or industry benchmark. Splitting the sample into smaller and larger firms (defined as firms below or above the median market capitalization of all CRSP stocks that month) or splitting the sample in halves by time period has also little effect on the results.

Columns 7 and 8 report results for portfolio sorted on one year customer returns. We skip a month between the sorting period and portfolio formation. Looking at one

[21] These 125 portfolios are reformed every month based on the market equity, M/B ratio, and prior year return from the previous month. The portfolios are equal weighted and the quintiles are defined with respect to the entire CRSP universe in that month.
[22] Industries are defined as in Fama and French (1997). All the results in the paper are robust to using alternative (coarser) industry classifications.

year customer momentum, the results do vary by firms' size. For equally weighted portfolios (or for smaller firms) the one year customer momentum is large and highly significant. The baselines rolling strategy earns returns of 1.13 % a month (t-statistic = 4.16). On the other hand, although returns of value weighted strategies (or larger cap stocks) are large in magnitude (the average return of the value weighted one-year customer momentum is about 70 basis point per month), we cannot reject the hypothesis of no predictability at conventional significance levels.

All of these results tell a consistent story: lagged customer stock returns predict subsequent stock returns of linked supplier firms. Prices react to news about firms' principal customers but later drift in the same direction. The drift is equally large (on average about 100 basis points per month) for both smaller and large cap securities, but its persistence is correlated with size: prices converge faster in large cap securities. For smaller firms or equally weighted portfolios, the predictable returns persist for over a year.

B. Fama MacBeth regressions: hedged returns

In this section we use a Fama and MacBeth (1973) cross sectional regression approach to isolate the return predictability due to customer-supplier links by hedging out exposure to a series of variables known to forecast the cross section of returns. We are interested in testing return predictability of individual stocks generated by firm specific news about linked firms, hence it is important to control for variables that would cause commonalities across asset returns.

We use Fama and MacBeth (1973) forecasting regressions of individual stock returns on a series of controls. The dependent variable is this month's supplier stock return. The independent variables of interest are the one-month and one-year lagged stock returns of the firm's principal customer. We include as controls the supplier firm's own one-month lagged stock return and one-year lagged stock return. These variables control for the reversal effect of Jegadeesh (1990) and for the price momentum effect of Jegadeesh and Titman (1993). We control for the industry momentum effect of Moskowitz and Grinblatt (1999) by using lagged returns of the firm's industry portfolio. We use lagged returns of the customer's industry portfolio to control for the cross industry momentum of Menzly and Ozbas (2006). Finally, we control for the intra-industry lead-lag effect of Hou (2006) by using suppliers and customer's industry size sorted portfolios. Following Hou (2006) we sort firms in each industry into three size portfolios (bottom 30%, middle 40%, and top 30%) according to end-of-June market capitalization and compute equally weighted returns. We use as controls the lagged returns of the small, medium and large industry portfolios corresponding to both the customer and supplier[23]. The loadings on these additional portfolios capture systematic lead-lag effects across or within industry. We also include (but we do not report in the tables) firms' size and book to market as additional controls.

Since we are running one-month ahead forecasting regressions, the time series of the regression coefficients can be interpreted as the monthly return of zero cost portfolio that hedges out the risk exposure of the remaining variables[24]. Nevertheless, achieving these returns is likely to be difficult since, although the weights of the long short portfolio sum up to zero, the single weights are unconstrained, hence the regression could call for extreme overweighting of some securities. To obtain feasible returns, we follow Daniel and Titman (2006) and we rescale the positive and negative portfolio weights so that the coefficients correspond to the profit of going long $1 and short $1 (either equally weighted or value weighted)[25]. Table VI reports 4-factor alphas of each of these portfolios. The returns in the table have the following interpretation: the profit of going long $1 and short $1 in a customer momentum strategy using all the available stocks in a single portfolio, after hedging out exposure to size, book to market, one-month reversals, price momentum, industry momentum, cross industry momentum and lead-lag effects.

[Insert table VI here]

The results in Table VI give an unambiguous answer: past customer returns forecast subsequent supplier stock returns. The effect is large, robust and is largely

---

[23] For brevity we only report coefficients on the small and large industry portfolios.
[24] See Fama (1976).
[25] See Daniel and Titman (2006).

unrelated to other documented predictability effects[26]. Using the full set of controls and value weighted portfolios, the average net effect in Table VI (after hedging) is around 88 basis points per month.

VI. Variation in inattention

If limited investor attention is driving the return predictability results, varying inattention should vary the magnitude and significance of the result. In this section, we use a proxy to identify subsets of firms where attention constraints are more (less) likely to be binding. We test the hypothesis that return predictability is more (less) severe for those firms in which it is more (less) likely that information is simultaneously collected about both linked firms, reducing the inattention to the customer-supplier link.

The proxy we use is "common ownership" (COMOWN). For every link relation, we use data on mutual fund holdings to compute common ownership COMOWN = (#COMMON / #FUNDS) defined as the number of mutual funds holding both the customer and the supplier (#COMMON) divided by the number of mutual funds holding the supplier over the same month (#FUNDS). COMOWN thus measures the fraction of all mutual funds owning the supplier firm that also own the customer. For example, suppose that at the end of month t, 100 mutual funds hold shares of XYZ. Firm XYZ's customer is ABC. If out of the 100 managers holding XYZ, 60 managers also hold shares of ABC, COMOWN for firm XYZ is given by 60/100 = 60%. To construct COMOWN, we extract quarterly mutual fund holdings from the CDA/Spectrum mutual funds database and match calendar month and quarter-end dates of the holdings assuming that funds do not change holdings between reports. The idea behind COMOWN is that mutual fund managers holding both securities in their portfolios are more likely to gather information or monitor more closely both the customer and the supplier. Thus, we expect information about related firms to be impounded quicker into prices for stocks with a higher fraction of common fund ownership.

Every calendar month, we use independent sorts to rank stocks in two groups

[26] Adding contemporaneous customer returns as a regressor to control for the indirect effect of the omitted contemporaneous customer returns has no effect on the results. For brevity we do not report these results, but they are available upon request.

(low and high) based on the measure COMOWN. We then perform the customer momentum strategy (long-short customer momentum portfolios) separately for each of the high COMOWN and low COMOWN groups. Our COMOWN measure is scaled by the number of funds to control for the fact that mutual funds tend to have portfolio weights tilted toward larger cap liquid securities; hence, our measure of common ownership is designed to control for liquidity and breadth of ownership issues[27]. In order to further ensure that the results are not driven by small cap illiquid securities, we also report long/short returns by size and total fund ownership.

We report results in Table VII. Consistent with the customer momentum returns being driven by investor inattention, varying inattention, as proxied by the fraction of common managers' holdings, significantly varies the returns to customer momentum. Looking at the universe of large cap securities (above the NYSE median) with fund ownership of at least 20 managers, the customer momentum portfolio for stocks with a low (or zero) overlap of common mutual fund managers (high inattention) delivers 2.70 % per month (t-statistic = 3.49, equally weighted), while the same zero cost portfolio for securities with a large amount of common ownership across funds (low inattention) generates 0.61% per month (t-statistic = 1.05). The spread in common ownership generates a significant spread in the returns to customer momentum (high inattention minus low inattention) of 2.09% per month (t-statistic = 2.42). Other results reported in Table IX show this same pattern: prices of suppliers with a lower fraction of managers holding shares of both customer and supplier underreact significantly more to news about related customers than suppliers who are not as commonly owned with their customers. The spread in customer momentum returns is large, on average 132 basis points per month, although as the returns are volatile, we are in some sub-samples unable to reject the null hypothesis that the returns are statistically different[28].

[Insert table VII here]

The results in Table VII lend support to the customer momentum returns

[27] The correlation between COMOWN and total mutual fund ownership is 7%.

[28] All of the point estimates of differences are in the same direction and are greater than 90 basis points per month. However, double sorting significantly reduces the number of stocks in each portfolio, substantially raising idiosyncratic volatility.

documented in Section IV and Section V being driven by investor inattention (as proxied by disjoint fund ownership). Furthermore, they provide some evidence consistent with high COMOWN managers keeping prices closer to fundamentals, as news about related firms appear to be impounded quicker into prices for stocks with a higher fraction of COMOWN.

As common holding managers are more likely to jointly monitor both customer and supplier, we would expect a common fund to promptly react and trade when information about a related firm is released into the market. On the other hand, managers that do not hold a firm's customer in their portfolio are more likely to initially overlook or react with a lag to news about a firm's principal customer, so will trade less promptly on these customer shocks. We now turn to a test of this hypothesis[29].

We test this implication by looking at net trading activity by mutual fund managers. For every stock in our sample, let the total number of shares (S) owned by the mutual fund sector at the end of quarter t be equal to S = CS +NCS where CS (common shares) is the total number of shares held by managers who also hold shares of the firm's principal customer, and NCS (non common shares) is the total number of shares held by managers who do not hold shares of the firm's principal customer. Net mutual fund purchases for stock j (NETBUY) in quarter t is given by

$$\begin{aligned} NETBUY_{jt} &= \frac{\Delta S_{jt}}{SHROUT_{t-1}} = \underbrace{\frac{\Delta CS_{jt}}{SHROUT_{t-1}}}_{NETBUY^{C}} + \underbrace{\frac{\Delta NCS_{jt}}{SHROUT_{t-1}}}_{NETBUY^{NC}} \\ NETBUY_{jt} &= NETBUY_{jt}^{C} + NETBUY_{jt}^{NC} \end{aligned} \quad (1)$$

where SHROUT is total shares outstanding. Equation (1) decomposes the total net purchase by mutual funds (as a fraction of shares outstanding) into net purchases by common (C) and non common managers (NC). We regress net purchases in quarter t on contemporaneous and lagged customer return (CRET), and a series of controls X[30], to estimate the sensitivity to linked customer news.

[29] We would like to thank Toby Moskowitz for suggesting this test.

[30] Controls include lagged customer and firm's own returns, industry returns, size, and book to market.

$$NETBUY_t^i = a + b_1^i CRET_t^i + \boldsymbol{\theta}^i \mathbf{X}_t^i + \upsilon_t^i \qquad i \in \{C, NC\} \qquad (2)$$

Under the null hypothesis that common managers are more likely to trade stocks in response to news about related firms we have $b_1^C > b_2^{NC}$. That is, ceteris paribus, we expect managers holding both firm XYZ and its customer ABC, to be more likely to purchase (sell) shares of XYZ in quarters when ABC experiences good (bad) news. Clearly, equation (2) is silent about causality. Although it could be that common managers react to shocks about related customers by purchasing more shares of the supplier, an alternative hypothesis is that, in a given quarter, common managers buy both suppliers and customers in tandem and the buying activity actually pushes both prices higher. Given the fact that we observe fund holdings at semi-annual or at most at quarterly level, we cannot distinguish between the two hypotheses. We simply test the hypothesis that, when compared to non common funds, common funds are more likely to be net purchasers (sellers) of a stock in quarters when linked firms experience large stock returns (controlling for the stock's own return), consistent with common ownership being a relaxation in the limited attention constraint.

We estimate equation (2) using Fama-MacBeth (1973) cross sectional regressions. Cross sectional regressions are run every quarter and Table VIII reports time series averages of the coefficients. The column "difference" tests the null hypothesis $b_1^C = b_2^{NC}$ [31]. Results in Table VIII show that common managers are more likely to be net purchasers (sellers) of stocks in quarters where their customer firms experience large positive (negative) returns, while non common managers are not significantly related to contemporaneous customer returns. Further, as conjectured, the difference $b_1^C - b_2^{NC}$ is positive and significant, indicating that common managers trade significantly more than non common managers on news about a linked customer firm. Figure 3 better illustrates the result by reporting how customer returns predict managers' trading activity at different horizons. We show the cumulative average returns in quarter *t+k* on the long/short customer momentum portfolios formed on customer returns in quarter *t*[32].

[31] We use the time series variation of the difference in the two coefficients to generate standard errors.
[32] These returns are the quarterly counterpart to Figure 2. At the beginning of every quarter, stocks are ranked in ascending order based on the return of a portfolio of its major customers at the end of the

We also plot mutual fund net purchases on the long/short customer momentum portfolio over time. Figure 3 shows that common funds immediately react to information that causes large swings in the stock price of their principal customers. Looking at the long/short portfolio, common funds tend to increase their holdings in quarter 0 (the sorting quarter), while non common managers show almost zero net trading. Net purchase by non common managers spikes in quarter 1, which is consistent with the hypothesis that managers not holding a firm's customers in their portfolio are more likely to initially overlook the impact of customer-related news and react with a significant lag (1 quarter).

[Insert figure 3 here]

Model 2 and 3 in Table VIII, show that controlling for the firm's own past returns non common managers net purchases are unrelated to both contemporaneous and lagged customer returns, while they are strongly related to the firm's own stocks return. Thus, given a customer shock at date t, it appears that that non common manager net purchases at date t+1 are entirely due to the fact the high returns of the customer at date t predict high supplier returns at t+1. Once controlling for the effect customer returns have on supplier's own returns, the marginal effect of customer returns on non common managers' net purchases is not significant.

[Insert table VIII here]

Taken jointly, the results in Tables VII and VIII, and Figure 5, lend support to the hypothesis of the customer momentum findings being driven by inattention, as proxied by cross ownership or cross trading by mutual fund managers, in that variation in inattention leads to variation in the extent of return predictability. Suppliers in which market participants are more likely to simultaneously collect information about

---

previous quarter. Stocks are assigned to one of five quintile portfolios. The figure shows average cumulative returns (in %) and mutual fund net purchases (in %) over time of a zero cost portfolio that holds suppliers with the top 20% customer return stocks and sells short suppliers with the bottom 20% customer return stocks.

linked customers, thus reducing “inattention” to the customer-supplier link, see both more timely trading on linked customer shocks, and less of a lag in price response to the shocks (so less return predictability).

VII. Real effects

We show a significant and predictable return in supplier firms, consistent with some investors ignoring material and publicly available customer-supplier links. The investor limited attention hypothesis is based on the assumption that investors should give attention to customer-supplier links. In this section we provide evidence to support this assumption. We exploit time variation in our customer-supplier links data and we show that firms’ real operations are significantly more correlated when they are linked, relative to periods when they are not linked. The real quantities we examine are sales and operating income. Panel A of Table IX gives the correlations between customer and supplier sales and operating income[33], both when the pair are linked and not linked. From Panel B, correlations and cross-correlations of all real quantities rise substantially when the customer and supplier are linked. The correlation of customer to supplier operating income, for example, increases by 38.7 % (t-statistic = 3.88), while the correlation of customer to supplier sales increases by 51.4 % (t-statistic = 8.55) when linked.

Panel C tests the ability of customer shocks today to predict future real shocks in supplier firms, both when customer-supplier are linked and not linked. We use a regression framework where we can control for industry and time effects. The dependent variables are suppliers’ future annual operating income and sales (both scaled by assets), and future monthly returns. The independent variable, CRET(t), is today’s customer return. The categorical variable LINK is equal to 1 when two firms are linked as customer-supplier, and zero otherwise. We include industry-pair by date fixed effects, defined as the distinct (Cus. Ind, Supp. Ind.) pair that exists between customer and supplier firms interacted with date (year or month). The coefficient on the interaction of CRET(t)*LINK(t) can be interpreted as the predictive power of customer shocks over

[33] Both of the real quantities are winsorized at the .01 level in the table. The results are not sensitive to logging the variables or using another winsorizing level.

subsequent suppliers profits and returns within a given industry-pair (ex. steel and automobiles) and year (ex. 1981), solely because the given set of firms are linked as opposed to not being linked.

[Insert table IX here]

The results in Column 1 and Column 2 of Panel C suggest that when customer-supplier are not linked, shocks to the customer do not have predictive power over future profits of suppliers. In contrast, when the two firms are linked (LINK*CRET), customer shocks today predict future real shocks in supplier firms. Column 3 presents similar evidence for returns.

This section presents evidence that firms' real operations and returns are significantly more related when the two firms are linked as customer and supplier as opposed to not linked. This lends support to the assumption, and affirms the intuition, that customer-supplier relationships generate significant co-movements in the underlying cash flows of the linked firms, and thus should be given attention by investors.

VIII. Conclusion

This paper suggests that investor limited attention can lead to return predictability across assets. We provide evidence consistent with investors displaying limited attention, with this limited attention having a substantial effect on asset prices. The customer-supplier links in the paper are publicly available and in some cases longstanding relationships between firms, with the given customer on average accounting for 20 % of the supplier's sales. Investors, however, fail to take these links into account, resulting in predictable returns by buying or selling the supplier firm following a positive or negative shock, respectively, to its customer. This customer momentum strategy yields large returns and is largely unaffected in both magnitude and significance by controlling for the 3-factor model, liquidity, own firm momentum, industry momentum, within industry lead-lag relationships, and across industry momentum. As well, we focus on short term predictability using monthly data, hence market microstructure noise typical of studies with daily or intra-daily data and asset pricing model misspecification problems related to long term studies are less likely to be an issue.

We believe the customer-supplier link provides a natural framework to test investor inattention. Not only is the link publicly available to all investors, but given our results on real effects of the link, it is difficult to argue that this link should not be taken into account when forming expectations about suppliers' future cash flows. More generally, customer-supplier limited attention poses a roadblock for standard asset pricing models. What we document is not an isolated situation or constrained to a few firms, but instead a systematic violation across firms having a material effect on prices. If it's true that investors ignore even these blatant links, then the informational efficiency of prices to more complex pieces of information is potentially less likely. We believe the avenue of future research in limited attention should examine to what extent different types of information and different delivery paths affect investors' attention, and how attention varies across other financial instruments or product markets. This could give us a better understanding of how investors process information and allow us to make richer empirical predictions about asset prices.

References

Badrinath, S., Kale, J., Noe, T., 1995, Of Shepherds, Sheep, and the Cross-autocorrelations in Equity Returns. Review of Financial Studies 8, 401-430.

Barber, B., Odean, T., 2006, All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, forthcoming.

Bartov, E., Bodnar, G., 1994, Firm valuation, earnings expectations, and the exchange-rate exposure effect. Journal of Finance 49, 1755-1785.

Brennan, M., Jegadeesh, N., Swaminathan, B., 1993, Investment Analysis and the Adjustment of Stock Prices to Common Information. Review of Financial Studies 6, 799-824.

Carhart, M., 1997, On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chan, K., Jegadeesh, N., Lakonishok, J., 1996, Momentum Strategies. Journal of Finance 51, 1681-1713.

Chordia, T., Swaminathan, B., 2000, Trading Volume and Cross-Autocorrelations in Stock Returns. Journal of Finance 55, 913-935.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998, Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839-1886.

Daniel, K., Titman, S., 1997, Evidence on the characteristics of cross sectional variation in stock returns. Journal of Finance 52, 1-33.

Daniel, K., Titman, S., 1998, Characteristics or covariances? Journal of Portfolio Management 24, 24-33.

Daniel, K., Titman, S., 2006, Market reactions to tangible and intangible information. Journal of Finance 61, 1605-1643.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997, Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035-1058.

DellaVigna, S., Pollet, J., 2007, Demographics and Industry Returns. American Economic Review, forthcoming.

DellaVigna, S., Pollet, J., 2006, Investor inattention, firm reaction, and friday earnings announcements. Unpublished working paper. UC Berkeley and University of Illinois.

Fama, E., MacBeth, J., 1973, Risk, return and equilibrium: empirical tests. Journal of Political Economy 81, 607-636.

Fama, E., 1976, Foundations of finance: portfolio decisions and securities prices. Basic Books Inc., New York.

Fama, E., French, K., 1993, Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E., French, K., 1997, Industry costs of equity. Journal of Financial Economics 43, 153-193.

Gabaix, X., Laibson, D., Moloche, G., Weinberg, S., 2006, Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model. American Economic Review 96, 1043-1068.

Grossman, S., Stiglitz, J., 1980, On the impossibility of informationally efficient markets. American Economic Review 70, 393-408.

Hirshleifer, D., Teoh, S., 2003, Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337-386.

Hirshleifer, D., Teoh, S., 2004, Limited investor attention and earnings-related under- and over-reactions. Unpublished working paper. Ohio State University.

Hirshleifer, D., Lim S., Teoh, S., 2003, Disclosure to a credulous audience: the role of limited attention. Unpublished working paper. Ohio State University.

Hirshleifer, D., Hou, K., Teoh, S., Zhang, Y., 2004, Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297-331.

Hong, H., Stein, J., 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143-2184.

Hong, H., Lim, T., Stein, J., 2000, Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Hong, H., Torous, W., Valkanov, R., 2005, Do industries lead the stock market? Journal of Financial Economics, forthcoming.

Hou, K., 2006, Industry information diffusion and the lead-lag effect in stock returns. Review of Financial Studies, forthcoming.

Hou, K., Moskowitz, T., 2005, Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18, 981-1020.

Hou, K., Peng, L., Xiong, W., 2006, A tale of two anomalies: the implication of investor attention for price and earnings momentum. Unpublished working paper. Ohio State University, Princeton University, and Baruch College.

Huberman, G., Regev, T., 2001, Contagious speculation and a cure for cancer: a non-event that made stock prices soar. Journal of Finance 56, 387-396.

Jegadeesh, N., 1990, Evidence of Predictable Behavior of Security Returns. Journal of Finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993, Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65-91.

Kahneman, D., 1973, Attention and effort. Prentice Hall, New Jersey.

Lo, A., MacKinlay, C., 1988, Stock market prices do not follow random walks: evidence from a simple specification test. Review of Financial Studies 1, 41-66.

Lo, A., MacKinlay, C., 1990, When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175-205.

Menzly, L., Ozbas, O., 2006, Cross-industry momentum. Unpublished working paper, University of Southern California.

Merton, R., 1971, Optimum consumption and portfolio rules in a continuous-time model. Journal of Economic Theory 3, 373-413.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483-510.

Moskowitz, T., Grinblatt, M., 1999, Do industries explain momentum? Journal of Finance 54, 1249-1290.

Pashler, H., Johnston J., 1998, Attentional limitations in dual-task performance. In: Pashler, H., (Ed.), Attention, Psychology Press.

Pastor, L., Stambaugh, R., 2003, Liquidity risk and expected stock returns, Journal of Political Economy 111, 642-685.

Peng, L., Xiong, W., 2006, Investor attention, overconfidence, and category learning. Journal of Financial Economics 80, 563-602.

Ramnath, S., 2002, Investor and analyst reactions to earnings announcements of related firms: an empirical analysis. Journal of Accounting Research 40, 1351-1376.

Table I: Summary statistics

This table shows summary statistics as of December of each year. Percent coverage of stock universe (EW) is the number of stocks with a valid customer-supplier link divided by the total number of CRSP stocks. Percent coverage of stock universe (VW) is the total market capitalization of stocks with a valid customer-supplier link, divided by the total market value of the CRSP stock universe. Market to book is the market value of equity divided by Compustat book value of equity. Size is the firm's market value of equity.

	Min	Max	Mean	Std Dev	median
Panel A: Time series (24 annual observations, 1981 – 2004)					
Number of firms in the sample per year	390	1470	918	291	889
Number of customers in the sample per year	208	650	433	116	411
Full sample % coverage of stock universe (EW)	13.2	31.3	20.3	5.2	19.8
Full sample % coverage of stock universe (VW)	29.1	70.7	50.7	11.9	48.4
Firm % coverage of stock universe (EW)	8.5	22.8	12.8	4.1	13.2
Firm % coverage of stock universe (VW)	3.3	20.0	9.2	4.5	9.2
Customer % coverage of stock universe (EW)	4.9	11.5	7.6	1.8	7.4
Customer % coverage of stock universe (VW)	26.4	66.5	46.5	11.3	43.5
% of firm-customer in the same industry	20.6	27.3	23.0	1.9	22.7
Link duration (years)	1.0	23.0	2.7	2.3	2.0
Panel B: Firms (Pooled firm–year observations)					
Firm size percentile	0.01	0.99	0.48	0.27	0.48
Customer size percentile	0.01	0.99	0.91	0.15	0.98
Firm book to market percentile	0.01	0.99	0.51	0.28	0.52
Customer book to market percentile	0.01	0.99	0.47	0.26	0.49
Number of customers per firm	1.00	20.00	1.60	1.09	1.00
Percent of sales to customer	0.00	100	19.80	17.05	14.68

Table II: Correlation between customer returns and supplier returns, 1981–2004

Spearman rank correlation coefficients are calculated over all months and over all available stocks for the following variables. CXRET is the monthly return of a portfolio of a firm's principal customers minus the CRSP value weighted market return. R12 is the stock's compounded return over the prior twelve months. Size is the log of market capitalization as of the end of the previous calendar month. B/M is book-market ratio, which is the market value of equity divided by Compustat book value of equity. The timing of B/M follows Fama and French (1993) and is as of the previous December year-end. IXRET is the (value weighted) stock's industry return minus the CRSP value weighted market return. CXIRET is the (value weighted) stock's customer industry return minus the CRSP value weighted market return. We assign each CRSP stock to one of 48 industry portfolios at the end of June of each year based on its four-digit SIC code.

	CXRET	XRET	R12	SIZE	B/M	IXRET	CXIRET
CXRET	1.000	0.122	0.016	0.000	0.023	0.218	0.282
RET		1.000	0.037	0.031	0.045	0.168	0.254
R12			1.000	0.267	0.075	0.008	0.046
SIZE				1.000	-0.264	0.005	0.043
B/M					1.000	0.022	0.042
IXRET						1.000	0.291
							1.000

Table III: Customer momentum strategy, abnormal returns 1981–2004

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month, stocks are ranked in ascending order on the basis of the return of a portfolio of its principal customers at the end of the previous month. The ranked stocks are assigned to one of 5 quintile 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 that holds the top 20% high customer return stocks and sells short the bottom 20% low customer return stocks. 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: value weights	Q1(low)	Q2	Q3	Q4	Q5(high)	L/S
Excess returns	-0.596	-0.157	0.125	0.313	**0.982**	**1.578**
	[-1.42]	[-0.41]	[0.32]	[0.79]	[2.14]	[3.79]
3-factor alpha	**-1.062**	**-0.796**	**-0.541**	-0.227	**0.493**	**1.555**
	[-3.78]	[-3.61]	[-2.15]	[-0.87]	[1.98]	[3.60]
4-factor alpha	**-0.821**	**-0.741**	-0.488	-0.193	**0.556**	**1.376**
	[-2.93]	[-3.28]	[-1.89]	[-0.72]	[1.99]	[3.13]
5-factor alpha	**-0.797**	**-0.737**	-0.493	-0.019	0.440	**1.237**
	[-2.87]	[-3.04]	[-1.94]	[-0.07]	[1.60]	[2.99]

Panel B: equal weights	Q1(low)	Q2	Q3	Q4	Q5(high)	L/S
Excess returns	-0.457	0.148	0.385	0.391	**0.854**	**1.311**
	[-1.03]	[0.38]	[1.01]	[1.01]	[2.04]	[4.93]
3-factor alpha	**-1.166**	**-0.661**	**-0.446**	-0.304	0.140	**1.306**
	[-5.27]	[-3.89]	[-2.74]	[-1.76]	[0.71]	[4.67]
4-factor alpha	**-0.897**	**-0.482**	-0.272	-0.224	0.315	**1.212**
	[-4.20]	[-2.89]	[-1.70]	[-1.28]	[1.61]	[4.24]
5-factor alpha	**-0.939**	**-0.549**	-0.239	-0.041	**0.420**	**1.359**
	[-4.61]	[-3.27]	[-1.38]	[-0.23]	[2.11]	[4.79]

Table IV: Underreaction coefficients

This table shows returns on the customer momentum portfolio and the corresponding underreaction coefficients. At the beginning of every calendar month, stocks are ranked in ascending order based on the return of a portfolio of its major customers at the end of the previous month. We use return of the customer portfolio times the total fraction of the firm's sales accounted for by the principal customers. Stocks are assigned to one of five quintile portfolios. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks with stock price greater than $5 at portfolio formation. Panel A reports the average cumulative returns on long/short portfolios formed on the firm customer return in month *t*. *CRET* is the customer return in month *t*. *CCAR* is the customer cumulative returns over the subsequent six months [*t+1,t+6*]. RET is the supplier's stock return in month t. CAR is the cumulative return over the subsequent six months. t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panel B reports the underreaction coefficients. URC (Underreaction Coefficient) is defined as the fraction of total returns from month *t* to month *t+6* that occurs in month *t* (URC = RET / (RET + CAR)). PERCSALE is the % of firms sales accounted for by the principal customer. T-statistics are shown below the coefficient estimates. In Panel B, the t-statistics represent the distance of the coefficient from 1, which is the case of no underreaction. 5% statistical significance is indicated in bold.

Panel A: Supplier and Customer Returns									
	All firms	Larger firms	Smaller firms	PERCSALES quintiles					
				1(low)	2	3	4	5(high)	5-1
PERCSALES	0.351	0.351	0.363	0.086	0.132	0.199	0.313	0.615	0.529
CRET	**6.791**	**6.795**	**7.026**	**3.979**	**4.710**	**5.035**	**6.170**	**9.600**	**5.620**
(sales weighted)	[42.51]	[41.74]	[41.55]	[30.26]	[28.78]	[42.43]	[41.52]	[43.99]	[3.42]
RET	**4.192**	**5.270**	**2.055**	**6.076**	**5.350**	**4.715**	**3.842**	**4.555**	-1.521
	[13.17]	[14.57]	[5.09]	[3.89]	[6.80]	[7.56]	[6.98]	[9.42]	[-1.09]
CCAR[*t+1,t+6*]	0.442	0.495	0.336	0.502	0.460	0.183	0.337	0.391	-0.111
	[1.59]	[1.72]	[1.12]	[1.24]	[1.50]	[0.63]	[1.13]	[0.88]	[-1.17]
CAR[*t+1,t+6*]	**2.799**	**2.383**	**3.854**	2.769	2.457	1.929	**3.163**	**3.892**	1.123
	[3.74]	[2.91]	[3.55]	[0.64]	[1.12]	[1.29]	[2.64]	[3.22]	[0.02]
Panel B: Underreaction coefficients									
URC_{cust}	0.939	0.932	0.954	0.888	0.911	0.965	0.948	0.961	0.073
	[1.53]	[1.70]	[1.15]	[1.40]	[1.78]	[0.70]	[1.30]	[0.98]	[0.91]
URC_{sup}	**0.600**	**0.689**	**0.348**	0.687	0.685	0.710	**0.548**	**0.539**	-0.148
	[5.71]	[3.89]	[8.15]	[0.92]	[1.58]	[1.81]	[4.52]	[5.76]	[-0.42]

Table V: Robustness tests

This table shows calendar time portfolio return. At the beginning of every calendar month, stocks are ranked in ascending order on the basis of the return of a portfolio of its principal customers in the previous month. The ranked stocks are assigned to one of 5 quintile portfolios. All stocks are value (equally) weighted within a given portfolio, and the overlapping portfolios are rebalanced every calendar month to maintain value (equal) weights. Panel A includes all available stocks with stock price greater than \$5 and satisfying the condition on the left hand side at portfolio formation. ME is the market value of equity in the prior calendar month. TURN is the average daily turnover in the prior year, where turnover is defined as volume divided by shares outstanding. NUMEST is the number of analysts providing forecasts of earnings per shares for the current fiscal year. Analysts forecasts are from I/B/E/S. IO is institutional ownership, defined as the total number shares owned by intuitions reporting common stocks holdings to the SEC as of the last quarter-end divided by the number of shares outstanding. Institutional holdings are from Thomson Financial. 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. Panel B reports additional robustness checks. We report returns of a value (VW) and equally weighted (EW) zero-cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer return stocks. "Liquid stocks" are stocks with strictly positive trading volume on every trading day over the previous 12 months. "Larger cap stocks" are all stocks with market capitalization above the median of the CRSP universe that month, smaller stocks are below median. DGTW characteristic-adjusted returns are defined as raw monthly returns minus the returns on an equally weighted portfolio of all CRSP firms in the same size, market-book, and one year momentum quintile. Industry adjusted returns are defined as raw monthly returns minus the returns of the corresponding industry portfolio. 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: value weighted returns, 1981 – 2004	5-factor alpha			Excess returns		
Restrict investment to:	Q1(low)	Q5(high)	L/S	Q1(low)	Q5(high)	L/S
Supplier's ME > customer's ME	-0.792	0.428	**1.220**	-0.298	1.047	**1.345**
	[-1.62]	[0.92]	[2.06]	[-0.52]	[1.88]	[2.29]
Supplier's TURN > customer TURN	**-0.781**	0.314	**1.095**	-0.008	**1.249**	**1.257**
	[-2.18]	[0.89]	[2.23]	[-0.01]	[2.41]	[2.73]
Supplier's NUMEST > customer NUMEST	**-1.245**	0.416	**1.661**	-0.550	**1.324**	**1.874**
	[-2.55]	[0.82]	[2.24]	[-0.95]	[2.18]	[2.65]
Supplier's IO > customer's IO	**-0.894**	0.049	**0.943**	0.054	**0.944**	**0.890**
	[-2.76]	[0.08]	[2.31]	[0.23]	[2.17]	[2.05]

Table V: Robustness tests (continued)

Panel B: L/S returns		1 month customer return						1 year customer return	
				Liquid stocks		Skip a week		Skip a month	
Weight	# months	VW	EW	VW	EW	VW	EW	VW	EW
Return	288	**1.578**	**1.311**	**1.377**	**1.046**	**1.464**	**0.932**	0.694	**1.13**
		[3.79]	[4.93]	[3.16]	[3.14]	[3.55]	[3.28]	[1.85]	[4.16]
DGTW	288	**1.121**	**0.839**	**0.873**	**0.955**	**1.061**	**0.634**	0.616	**0.737**
		[3.23]	[3.23]	[2.33]	[3.19]	[3.05]	[2.53]	[1.78]	[2.90]
Smaller firms	288	**1.487**	**1.071**	0.584	0.610	**1.266**	**0.879**	**1.093**	**1.216**
		[3.95]	[3.06]	[0.53]	[0.57]	[3.69]	[2.45]	[3.13]	[3.66]
Larger firms	288	**1.475**	**1.336**	**1.405**	**1.096**	**1.375**	**1.243**	0.524	**0.987**
		[3.70]	[4.21]	[3.26]	[3.45]	[3.29]	[3.87]	[1.41]	[3.19]
1981 – 1992	144	**1.963**	**1.391**	0.501	0.550	**1.763**	**0.943**	0.237	**1.137**
		[4.39]	[4.28]	[0.76]	[0.79]	[4.08]	[2.95]	[0.67]	[3.63]
1993 - 2004	144	**1.266**	0.698	**1.367**	**1.034**	1.161	**0.871**	1.081	**1.153**
		[1.99]	[1.66]	[3.12]	[3.08]	[1.72]	[1.96]	[1.77]	[2.75]
Industry adjusted	288	**0.975**	**0.508**	**0.812**	**0.711**	**0.882**	**0.529**	0.500	**0.698**
		[2.89]	[2.14]	[2.23]	[2.51]	[2.55]	[2.25]	[1.41]	[3.24]
Different industry	288	**1.157**	**1.162**	**1.240**	**1.212**	**1.023**	**0.883**	**0.817**	**0.945**
		[4.83]	[2.84]	[2.57]	[3.68]	[3.43]	[3.01]	[2.03]	[3.97]
Same industry	288	**1.288**	**1.192**	**1.938**	**1.372**	**1.173**	**0.901**	0.705	0.349
		[2.49]	[2.90]	[3.53]	[2.69]	[2.34]	[2.90]	[1.42]	[0.90]

Table VI: Cross sectional regressions, hedged returns

This table reports monthly abnormal returns of portfolio constructed using Fama-MacBeth forecasting regressions of individual stock returns. The dependent variable is the monthly stock return. The explanatory variables are the lagged customer return (CRET), the stock's own lagged return (RET), lagged return of the corresponding industry portfolio (INDRET), lagged return of the corresponding customer industry portfolio (CINDRET), lagged returns of the corresponding size sorted small (P1_IRET) and large (P3_IRET) industry portfolio, and lagged returns of the corresponding customer size sorted small (P1_CIRET) and large (P3_CIRET) industry portfolio. To compute size sorted portfolio we sort firms in each industry into three size portfolios (P1 bottom 30%, P2 middle 40%, and P3 top 30%) according to end-of-June market capitalization and compute equally weighted returns. Firms size (log of market equity), book to market, one month size sorted medium (P2) industry and customer industry portfolio, one year size sorted small (P1), medium (P1) and large (P3) industry and customer industry portfolios are included in the regressions but not reported. Cross sectional regressions are run every calendar month. We rescale the portfolio weights to correspond to the profit of going long $1 and short $1 (either equally weighted or value weighted). Abnormal returns are 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 and Carhart (1997) momentum factor. Returns are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

	Equal weights					Value weights				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CRET_{t-1}$	**0.895**	**0.730**	**0.724**	0.445	**0.730**	**1.170**	**1.151**	**1.178**	**0.855**	**0.876**
	[4.03]	[2.99]	[3.01]	[1.83]	[2.68]	[3.57]	[3.10]	[3.26]	[2.26]	[3.22]
$CRET_{t-12,t-2}$	**0.529**	**0.598**	**0.604**	**0.529**	0.220	-0.136	-0.029	-0.043	-0.102	-0.134
	[2.88]	[2.80]	[2.83]	[2.44]	[1.20]	[-0.43]	[-0.08]	[-0.12]	[-0.29]	[-0.41]
RET_{t-1}	**-0.862**		**-0.866**	**-1.005**	**-1.089**	-0.119		0.026	-0.079	-0.386
	[-2.69]		[-2.69]	[-3.22]	[-3.88]	[-0.32]		[0.07]	[-0.22]	[-1.15]
$RET_{t-12,t-2}$	0.344		0.167	0.194	0.100	-0.071		0.373	0.283	-0.012
	[1.22]		[0.53]	[0.62]	[0.36]	[-0.19]		[0.86]	[0.66]	[-0.03]
$INDRET_{t-1}$		**0.791**	**0.819**	**0.518**			0.297	0.243	0.098	
		[3.04]	[3.32]	[2.33]			[0.87]	[0.74]	[0.30]	
$INDRET_{t-12,t-1}$		0.208	0.219	0.18			-0.286	-0.271	-0.28	
		[0.92]	[0.97]	[0.85]			[-0.79]	[-0.73]	[-0.80]	
$CINDRET_{t-1}$				**1.407**					**1.096**	
				[4.92]					[3.35]	
$CINDRET_{t-12,t-1}$				-0.38					0.202	
				[-1.79]					[0.62]	
$P1\_INDRET_{t-1}$					0.198					-0.074
					[1.06]					[-0.27]
$P3\_INDRET_{t-1}$					**0.820**					0.486
					[3.82]					[1.63]
$P1\_CINDRET_{t-1}$					0.234					-0.087
					[1.07]					[-0.28]
$P3\_CINDRET_{t-1}$					**0.599**					0.548
					[3.26]					[1.76]

Table VII: Mutual fund common ownership, customer momentum returns

This table shows calendar time portfolio return. At the beginning of every calendar month, stocks are ranked in ascending order on the basis of the return of a portfolio of its principal customers in the previous month. The ranked stocks are assigned to one of 5 quintile portfolios. The portfolio include all available stocks with stock price greater than $5 at portfolio formation. Stocks are further split in two groups (above and below median), based on COMOWN. For each supplier "common ownership" COMOWN = (#COMMON/#FUNDS) is defined as the number of mutual funds holding both the customer and the supplier in that calendar month (#COMMON) divided by the number of mutual funds holding the supplier over the same month (#FUNDS). All stocks are value (equally) weighted within a given portfolio, and the overlapping portfolios are rebalanced every calendar month to maintain value (equal) weights. We report returns of a value (VW) and equally weighted (EW) zero-cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer return stocks. Returns are in monthly percent, t-statistics are shown below the coefficient estimates. 5% statistical significance is indicated in bold.

			At least 20 mutual funds holding the stock							
	All stocks		All stocks		At least 10 common funds		Larger firms (CRSP median)		Larger firms (NYSE median)	
Weight	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Low COMOWN	**1.653**	**2.301**	**1.659**	**2.306**	1.469	**1.889**	**1.572**	**2.288**	**2.703**	**2.852**
Lower percent of common ownership	[5.46]	[5.24]	[2.96]	[3.64]	[1.75]	[2.08]	[2.82]	[3.60]	[3.49]	[3.55]
High COMOWN	**0.750**	**1.098**	0.528	0.736	0.532	0.835	0.407	0.732	0.611	**1.278**
Higher percent of common ownership	[1.97]	[2.17]	[0.98]	[1.23]	[0.85]	[1.21]	[0.75]	[1.22]	[1.05]	[2.11]
High-Low	**-0.903**	**-1.203**	-1.131	**-1.571**	-0.937	-1.054	-1.165	**-1.557**	**-2.093**	-1.575
	[-2.08]	[-1.99]	[-1.60]	[-1.98]	[-0.92]	[-0.95]	[-1.66]	[-1.96]	[-2.42]	[-1.71]

Table VIII: Mutual fund common ownership, net purchases

This table reports quarterly Fama-MacBeth regressions of mutual fund manager net buying activity. The dependent variable (NETBUY) is the aggregate quarterly net purchase of mutual fund managers. For a given stock, $NETBUY^{C}$ is defined as $NETBUY^{C} = \Delta CS_t / SHROUT_{t-1}$ where ΔCS_t is the change on total number of shares owned by mutual fund managers that also hold the customer in their portfolio in a given quarter. SHROUT is shares outstanding. $NETBUY^{NC}$ is defined as $NETBUY^{NC} = \Delta NCS_t / SHROUT_{t-1}$ where ΔNCS_t is the change on total number of shares owned by mutual fund managers that do not hold the customer in their portfolio. The explanatory variables are the contemporaneous and the lagged customer return (CRET), the stock's own contemporaneous and lagged return (RET), return of the corresponding industry portfolio (INDRET), the stock's market capitalization (ME) and market to book ratio (BM).

$$NETBUY_t^i = a + b_1^i CRET_t^i + \boldsymbol{\theta}^i \mathbf{X}_t^i + \upsilon_t^i \qquad i \in \{C, NC\}$$

Cross sectional regressions are run every calendar quarter and the estimates are weighted by the cross sectional statistical precision, defined as the inverse of the standard error of the coefficients in the cross sectional regressions. Cross sectional standard errors are adjusted for heteroskedasticity. The column "difference" tests the null hypothesis $b_1^{C} = b_2^{NC}$. Fama-MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

	(1)			(2)			(3)		
	$NETBUY^{C}$	$NETBUY^{NC}$	diff	$NETBUY^{C}$	$NETBUY^{NC}$	diff	$NETBUY^{C}$	$NETBUY^{NC}$	diff
$CRET_t$	**0.240**	-0.052	**0.292**	**0.248**	-0.342	**0.590**	**0.206**	-0.287	**0.493**
	[2.66]	[-0.32]	[2.53]	[2.44]	[-1.73]	[2.58]	[1.99]	[-1.52]	[2.18]
$CRET_{t-1}$	0.218	**0.282**		**0.242**	-0.104		**0.236**	-0.120	
	[1.92]	[2.60]		[2.14]	[-0.57]		[2.06]	[-0.66]	
$CRET_{t-5,t-2}$	0.047	0.041		0.051	-0.039		0.046	-0.035	
	[0.80]	[0.46]		[0.77]	[-0.41]		[0.71]	[-0.35]	
RET_t				**0.377**	**1.355**		**0.376**	**1.327**	
				[4.40]	[9.00]		[4.28]	[8.90]	
RET_{t-1}				**0.267**	**0.889**		**0.267**	**0.885**	
				[3.73]	[6.25]		[3.59]	[6.25]	
$RET_{t-5,t-2}$				**0.078**	**0.245**		**0.069**	**0.247**	
				[2.83]	[5.09]		[2.55]	[4.89]	
$IRET_{t-5,t}$							0.170	-0.084	
							[1.69]	[-0.45]	
M/B				-0.025	-0.085		-0.028	-0.078	
				[-1.01]	[-1.66]		[-1.09]	[-1.48]	
$\log(ME_t)$				0.020	-0.008		0.020	-0.009	
				[1.15]	[-0.30]		[1.14]	[-0.33]	
R^2	0.021	0.024		0.026	0.030		0.026	0.030	

Table IX: Real effects of company links

This table presents the effect of company links on the real quantities of firm sales and operating income. Panel A presents correlation matrices of annual sales and operating incomes of customers and suppliers, along with lagged year customers' sales and operating income. Link year is defined for each customer-supplier pair as a year when the supplier reports the given customer as a major customer (major customer is defined in text). Non-link year is a year when the customer and supplier are not linked in the data. Panel B reports differences between link and non-link year correlations. Panel C reports predictive regressions of supplier real quantities and returns on past customer shocks. Both sales and operating income are scaled by firm assets and are annual figures, while returns are monthly to keep comparability to previous tables. CRET is the customer returns in the prior year for the annual variables and prior month for the return regressions. All variables in the table are winsorized at the 1 percent level throughout the table. The results are not sensitive to logging or using other winsorizing cutoffs. All regressions include industry-pair by date (year and month, respectively) fixed effects. Industry-pair is defined as the pairing of industries to which the customer and supplier, respectively, belong in the customer-supplier relationship. The regressions are estimated with constants, which are not reported. Standard errors are adjusted for clustering at the yearly or monthly level. T-statistics calculated using the robust clustered standard errors are reported in parentheses. 5% statistical significance is indicated in bold.

OI_L^{Sup} =	Operating Income of Supplier / Assets Linked	S_L^{Cus} =	Sales of Customer Linked
/ OL_{NL}^{Sup} =	Operating Income of Supplier /Assets Not Linked	S_{NL}^{Cus} =	Sales of Customer Not Linked

Panel A – Correlations of Real Quantities						Panel B – Differences In Correlations (Linked – Not Linked)		
Linked			Not Linked			Correlation	(Linked - Not Linked)	% Increase When Linked
	OI_L^{Sup}	S_L^{Sup}		OI_{NL}^{Sup}	S_{NL}^{Sup}			
OI_L^{Cus}	0.275	0.358	OI_{NL}^{Cus}	0.199	0.222	(OI^{Sup}, OI^{Cus})	**0.077** [3.88]	38.7%
S_L^{Cus}	0.315	0.428	S_{NL}^{Cus}	0.237	0.283	(S^{Sup}, S^{Cus})	**0.145** [8.55]	51.4%

Table XI: Real effects of company links (continued)

Panel C – Real Effects of Customer Shocks – Linked and Not Linked						
	(1)		(2)		(3)	
Dependent variable	Operating Income/Assets (t+1)		Sales/Assets (t+1)		Returns(t+1)	
	CRET(t)	-0.004	CRET(t)	-0.011	CRET(t)	**0.012**
		[-0.77]		[-0.84]		[2.22]
	LINK* CRET(t)	**0.024**	LINK* CRET(t)	**0.072**	LINK* CRET(t)	**0.016**
		[3.00]		[2.91]		[2.20]
Ind-Pair-Date Fixed Effects		Yes		Yes		Yes
R^2		0.422		0.540		0.339

Figure 1: Coastcast Corporation and Callaway Golf Corporation

This figure plots the stock prices of Coastcast Corporation (ticker = PAR) and Callaway Golf Corporation (ticker = ELY) between May and August 2001. Prices are normalized (05/01/2001 = 1).

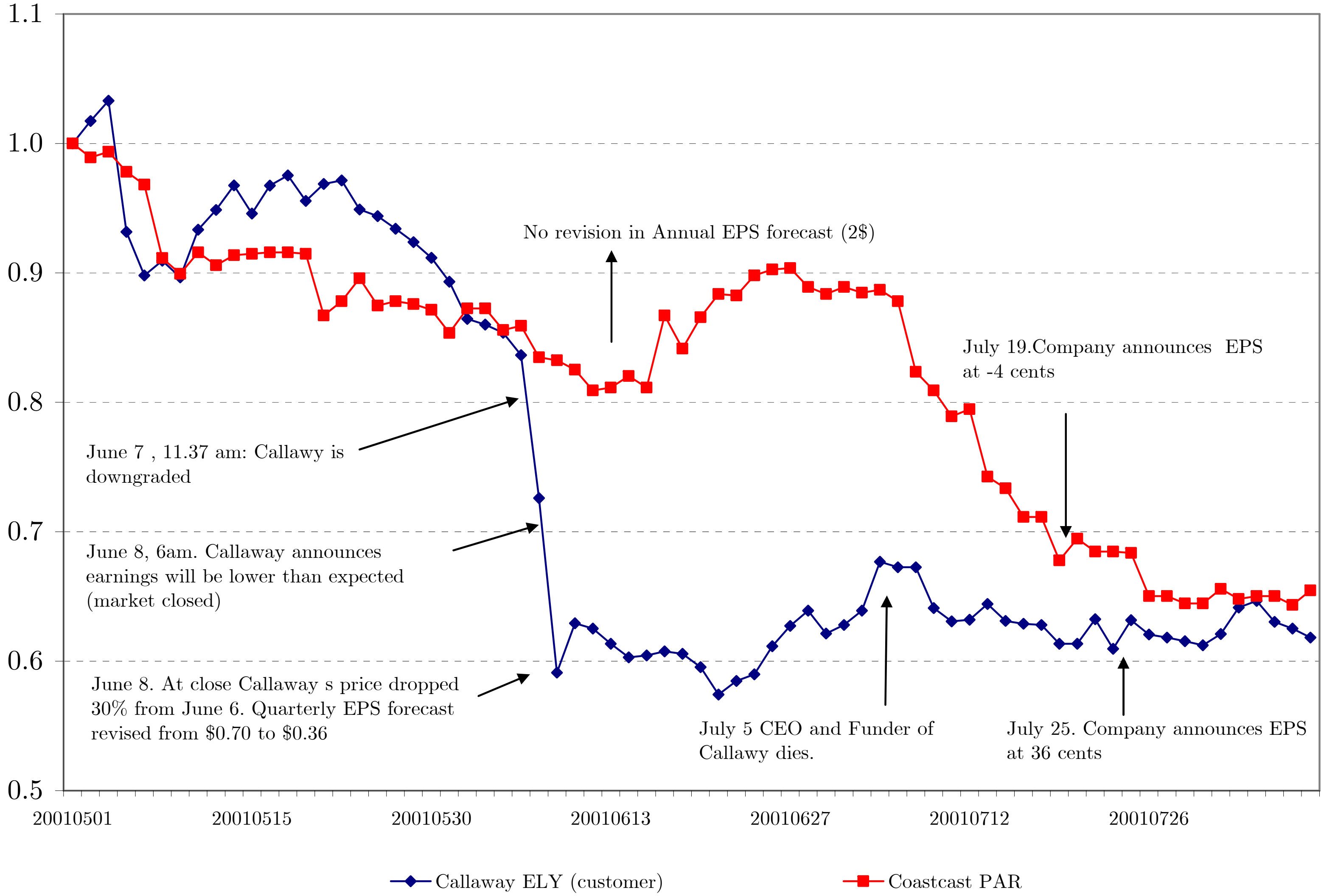

Figure 2: Customer momentum, event-time CAR

This figure shows the average cumulative return in month $t+k$ on a long/short portfolios formed on the firm customer return in month t. At the beginning of every calendar month, stocks are ranked in ascending order based on the return of a portfolio of its major customers at the end of the previous month. Stocks are assigned to one of five quintile portfolios. The figure shows average cumulative returns (in %) over time of a zero cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer returns stocks.

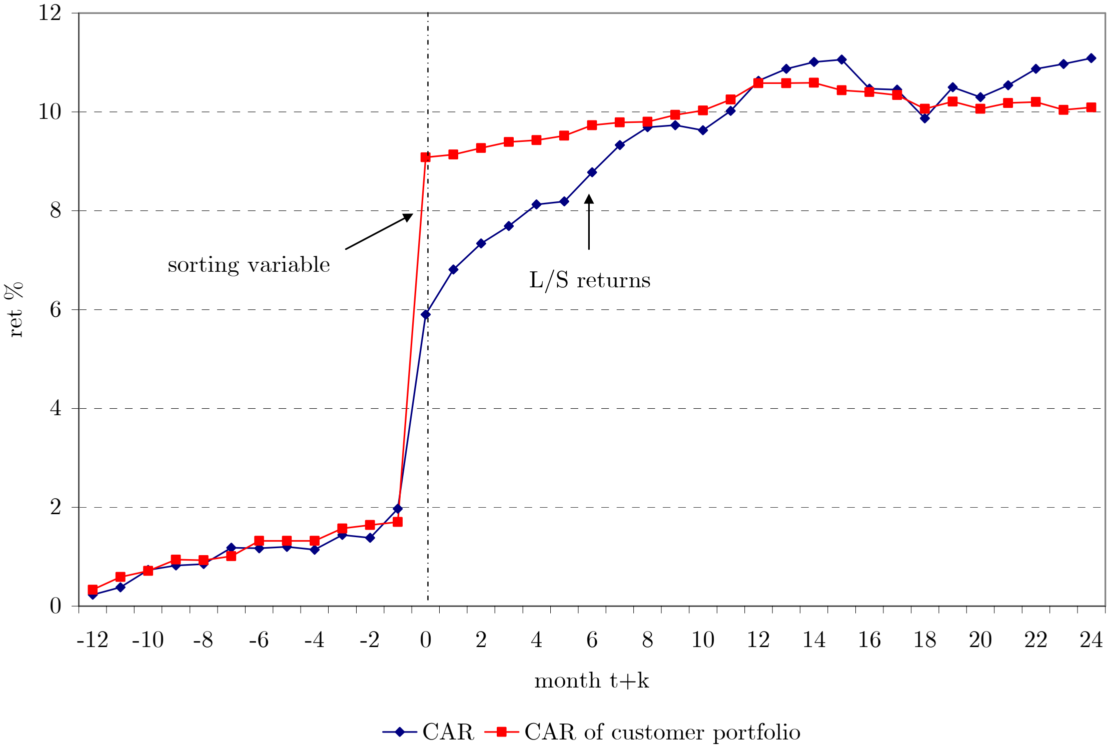

Figure 3: Customer momentum, event-time CAR and mutual fund's net purchases

This figure shows the average cumulative return and mutual funds net purchases in quarter *t+k* on a long/short portfolio formed on the firm customer return in quarter *t*. At the beginning of every quarter, stocks are ranked in ascending order based on the return of a portfolio of its major customers at the end of the previous quarter. Stocks are assigned to one of five quintile portfolios. The figure shows average cumulative returns (in %) over time of a zero cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer returns stocks, and the average net purchases by common and non common funds. For a given stock NETBUY COMMON is defined as $\Delta CS_t / SHROUT_{t-1}$ where ΔCS_t is the change on total number of shares owned by mutual fund managers that also hold the customer in their portfolio in a given quarter. SHROUT is shares outstanding. NETBUY NON COMMON is defined as $\Delta NCS_t / SHROUT_{t-1}$ where ΔNCS_t is the change on total number of shares owned by mutual fund managers that do not hold the customer in their portfolio.