Economic Links and Predictable Returns*

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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, or over 18 percent per year.

JEL Classification: G10, G11, G14

Key words: Economic links, customers, suppliers, inattention, momentum

I. Introduction

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, it's clear that the partner firms are stakeholders in each others' operations. Thus, any shock to one of the firms has a resulting effect on its linked partner. From this starting point, we examine how shocks to one firm in the relationship 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 a more difficult condition 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

[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 III.

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, many of the customer-supplier links are longstanding relationships and 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 in 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 cross sectional differences in 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 total sales. On July 7 at 11:37 am, Callaway was downgraded by one of the analysts covering it. In a press release on the next day (June 8, 6 am) 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 July 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 19, 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

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

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

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 Callaways'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 per year. We refer to this return predictability as "customer momentum". Moreover, return the customer momentum strategy has 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 customers. 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 (Grinblatt and Moskowitz (1999)) or by a lead-lag relationship within industries (Moskowitz and Hou (2005) and Hou (2005)). As evidence against these explanations driving the result, 78% of the customer-supplier link relationships are in fact across industries, so industry momentum is unlikely to be driving the results. Not surprisingly then, controlling for both of these effects does not have an impact on the magnitude or the significance of the customer momentum result. Finally, a recent paper by Menzly and Ozbas (2005) uses upstream and downstream definitions of industries to define cross-industry momentum. We find that controlling for cross-industry momentum 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 holding to identify a subset of firms where investors are, a priori, more or less likely to collect information on both customer and supplier. We show that return predictability is indeed more (less) severe where inattention constraints are more (less) likely to be binding.

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 II provides a brief background and literature review. Section III describes the data, while Section IV details the predictions of the limited investor attention hypothesis. Section V establishes the main customer momentum result. Section VI provides robustness checks and considers alternative explanations. Section VII examines the real effects of the customer-supplier link. Section VIII concludes.

II. 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). In his model, investors only obtain information on a small number of stocks. Investors then only trade on those stocks about which they are informed, so that stocks with less information and fewer traders sell at a discount stemming from the inability of these investors to share the risks of their holdings in these stocks. 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 Xiong and Peng (2005) 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. Xiong and Peng (2005) 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 firm price delay and find that these measures help to explain (or cause variation) in

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

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 (2005) find 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. DellaVigna and Pollet (2005) 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. 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 (2005). 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 (2005) use upstream and downstream definitions of industries and present evidence of cross-industry momentum. While both papers provide valuable evidence on slow diffusion of information, our approach is different. We do not restrict the analysis to specific industries or specific link 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.

III. Customer data

The data is obtained from several sources. Regulation SFAS No. 131 require firms to report selected information about operating segments in interim financial reports issued to shareholders. In particular, firms are required 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 consist 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 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-matched 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 customer 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 yearend 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 to 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.

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[4] Prior to 1997, Regulation SFAS No. 14 governed segment disclosure. SFAS No. 131, issue by the FASB in June 1997, was effective for fiscal years beginning after December 15, 1997.
[5] CRSP share code 10 and 11.
[6] We would like to thank Husayn Shahrur and Jayant Kale for making some of the customer data available to us.
[7] We use a "soundex" algorithm to generate a list of potential matches.

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 of 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. We plot the distribution of market capitalization of our sample in Figure 2.

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.

IV. Limited attention hypothesis and under-reaction

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*

[8] See, for example Fama ands French (1993).
[9] The assign stocks to 48 industries based on their SIC code. The industry definitions are from Ken French's website.

underreact to positive news involving related firms, and in turn generate positive subsequent price drift

In a world there 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 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

[10] Using different weighting scheme 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.

(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 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. A natural extension would be look at predictability from supplier to customer as well. Unfortunately, the current financial regulation 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 tests are in the direction of suppliers' stock price response to customers' shocks.

V. Results

Table II reports correlations between the variables we use to group stocks into portfolios. The correlations are based on monthly observation 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, marke to book ratios (market value of

[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.

equity divided by Compustat book value of equity) and the stock's return over the previous calendar year.

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. The highest correlations (0.29 and 0.26) are between customer returns, the firm's industry returns and the customer's industry returns. 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 VI we specifically address this issue by calculating abnormal returns of our test portfolios after hedging out inter and intra industry exposure.

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. 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 a staggering 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 earn abnormal returns of 1.37% per months (t-statistic = 3.12). The results show that even after controlling for past returns, high (low) customer momentum stocks earn high (low) subsequent returns. We return on 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 stocks prices to new information when bad news arrives. Using equal weight rather than value weights delivers similar results: the baseline customer momentum portfolio earns a monthly alpha of 1.3% (t-statistic = 4.93).

Table IV reports factors loadings for the calendar time portfolios. Consistent with the results in Table II, the portfolios have similar exposure to traded factors. None of the factor loadings is significant for the long/short customer momentum portfolio, which is consistent with returns being driven by under-reaction to the initial news content, rather than reflecting systematic risk. These results are consistent with the hypothesis LA: stocks prices drift after large price movements of related firms. Furthermore, the subsequent price drift is related to the magnitude of the initial customer return.

Figure 3 better 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 3 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 raise by 3.9% in month zero, where the 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.

In Table V 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 (sale-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 "Under-Reaction" 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 under-reaction 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 under-reaction or a sluggish stock price response to news about customers. Conversely, values of URC greater then one indicate the presence of overreaction to the initial news content embedded in the customer return[12].

The results in Table V show than on average stock prices under-react 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 and not statistically different from one. Another way to see this, from Panel A of Table V, is that customers do not have a significant CCAR following the initial price jump. That is, while information that generates large price movement for the customer is

[12] We would like to thank Owen Lamont for suggesting this measure.

quickly impounded into the customer's stocks 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 under-reaction coefficients tends 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 the Section VI. 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 Table III to Table V and Figure 3 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 stocks price adjusts only partially. Conversely, when a portfolio of customers experience large negative returns in a given month, stocks 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.

VI. Robustness Tests

A. Nonsynchronous trading, characteristics and size

Although the results are consistent with the LA hypothesis, there are a number of other plausible explanations of the data. Table VI shows results for a series of robustness test. In the Table we show average monthly return of the long/short customer momentum portfolio. In column 1 to 4 we report return of portfolios sorted on lagged 1-month customer return.

Nonsynchronous trading can generate positive autocorrelation across stocks.[13] 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 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.

Daniel and Titman (1998a, 1998b) 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)[14]. We industry-adjust returns in a fashion similar using the 48 matching industry portfolios[15]. The results in Table VI show that firms whose customer experienced good (bad) news out (under) perform their corresponding characteristic portfolios or industry benchmark. Splitting the sample into smaller and larges 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 no effect on the results.

Columns 5 and 6 report results for portfolio sorted on one year customer returns. We skip a month between the sorting period and portfolio formation. Looking at one 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.

Table VI reports additional robustness checks. All the results tell a consistent story: lagged customer stock returns predict subsequent stock returns of related firms.

[13] Lo and MacKinlay (1990).

[14] 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.

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 know to have forecasting power for 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-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 also 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 Grinblatt and Moskowitz (1999) and the intra-industry lead-lag effect of Hou(2005) by using lagged returns of the firm's industry portfolio. Finally, we use lagged returns of the customer's industry portfolio to control for the cross industry momentum of Menzly and Ozbas (2005). We include (but we do not report) firms' size as an additional control.

Table VII reports the time series averages of the coefficients. We weight the estimates by the cross sectional statistical precision, defined as the inverse of the standard errors the coefficients in the cross sectional regressions. Table VIII reports the risk-adjusted returns of the portfolios implicit in the Fama MacBeth analysis. Since we

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[15] Industry are defined as in Fama and French (1997).

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[16]. 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 (2005) 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)[17]. Table VIII 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, after hedging out exposure to size, book to market, one-month reversals, price momentum, industry momentum and cross industry momentum. In other words, they quantify the customer return predictability that is unrelated to these factors. A major difference between the returns in Table VIII and the returns in Table III is that we now include all the available stocks in one portfolio.

The results in Table VII and VIII give an unambiguous answer: past customer returns forecast subsequent supplier stock returns. The effect is large, robust and is almost unrelated to other documented predictability effects. Using the full set of controls and value weighted portfolios, the average net effect in Table VIII (after hedging) is around 100 basis points per month.

C. Variation In Inattention

If limited investor attention is driving the return predictability results we find, it should be true that varying inattention varies 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

[16] See Fama (1976).
[17] See Daniel and Titman (2005).

information is simultaneously collected about both linked firms, reducing the inattention to the customer-supplier link.

The proxy we use is COMMON. For every link relation, we use data on mutual fund holdings to compute COMMON, which is equal to the number of fund holdings both securities in their portfolio in that calendar month. The idea behind COMMON is that mutual funds managers holding both securities in their portfolios are more likely to gather information or monitor more closely both the customer and the suppliers, and their link. Thus we expect information about related firms to be impounded quicker into prices for stocks with a high number of common fund ownership.

To construct COMMON, 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 mutual funds do not change holdings between reports. Table IX reports results of these tests. Every calendar month, we use independent sorts to ranks stocks in three groups (low 30%, mid 40% and high 30%) in terms of COMMON, and we then compute long-short customer momentum portfolios within each of the three categories. By constructing long-short portfolios within ownership categories we sidestep liquidity and breadth of ownership issues, as our long-short portfolios have roughly a zero loading on these.

The results are in Table IX. Consistent with the customer momentum returns being driven by investor inattention, varying inattention significantly affects returns. For stocks with a low (or zero) overlap of common mutual fund managers (high inattention) the customer momentum returns are 3.02 % per month (t-statistic = 2.70) (value weighted), while for stocks with a large amount of common ownership across funds (low inattention) the returns are only 0.55 % per month and not statistically different from zero (t-statistic = 0.58). The spread in inattention causes a significant spread in the returns to customer momentum (high inattention – low inattention) of 2.48 % per month (t-statistic = 1.98). These results lend support to the significant customer momentum returns documented in Section V and Section VI being driven by investor inattention.

VII. Real Effects

We have thus far in the paper shown a significant and predictable return in supplier firms, consistent with investors ignoring material and publicly available customer-supplier links. The investor limited attention explanation we have conjectured is based on the assumption that investors should give attention to the customer-supplier link. In this section we provide evidence to support this assumption. We exploit time variation in our link data and we show that firms' real operations are significantly more correlated when they are linked, relative to periods when they are not linked. We restrict the sample for these tests to those firms that are linked at some point in the sample period. This should allow us to get a less noisy estimate of the effects of solely the same firm pairs being linked or not linked, abstracting from other firm characteristics that determine the likelihood of being linked at all. The real quantities we examine are sales and operating income. Panel A of Table X gives the correlations between customer and supplier sales and operating income[18], 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[19]. 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 and return shocks in supplier firms, both when customer-supplier are linked and not linked. We test this relation in a regression framework where industry and time effects can be controlled for. The regressions now use the real quantities scaled by assets to also alleviate any industry specific relation between customer and supplier assets. The dependent variables are suppliers' future scaled real quantities of operating income and sales, and future monthly returns. The independent variable, CRET(t), in each regression is then today's customer return. The categorical variable LINK is equal to 1

[18] 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.
[19] The t-statistics of the correlations are not shown for space, but all correlations in Panel A are significant at the 99% level.

when two firms are linked as customer-supplier, and zero otherwise. The interaction term LINK*CRET(t) then measures the effect of the customer-supplier being linked on the ability of customer shocks today to predict future supplier shocks. We include industry-pair by date fixed effects. Industry-pair is defined as the distinct (Cus. Ind, Supp. Ind.) pair that exists between customer and supplier firms. This is then interacted with date (year or month) to get the industry-pair-date fixed effect. This fixed effect should capture any relation specific to a certain industry pairing (ex. steel and automobiles), and any date specific shock that occurred to the pairing. It thus controls for any within industry, or upstream-downstream shocks that occurred in any given pair of industries at any given time. The coefficient on the interaction of CRET(t) and LINK can therefore be interpreted as the increased ability of customer shocks to have predictive power of future supplier real quantities and supplier returns within that industry-pair (ex. steel and automobiles) and year (ex. 1981), solely because the given set of firms were linked as opposed to not being linked.

The results in Column 1 and Column 2 of Panel C suggest that controlling for industry-pair-date effects when customer-supplier are not linked, shocks to the customer do not have predictive power over future real quantities of suppliers. In contrast, when the two firms are linked (LINK*CRET(t)), customer shocks today do have a significant ability to predict future real shocks in supplier firms. Column 3 presents similar evidence for returns. Customer shocks have a significantly larger effect on the future returns of suppliers when customer-supplier are linked (LINK*CRET(t)). In fact, the sensitivity of future suppliers' returns to today's customer returns over doubles when the two firms are linked as opposed to not linked.

This section has thus given 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 material customer-supplier relationships do have significant impacts on the relation between 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 substantive effect on asset prices. The customer-supplier links in the paper are publicly available and often 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 over a 20% return per year and is largely unaffected in both magnitude and significance by controlling for the 3 factor model, 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 important link should be not taken into account when forming expectations about suppliers' future cash flows. More generally, customer-supplier limited attention poses a large 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 asset 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 information delivery paths affect investors' attention. As well, whether attention to types of information varies across other financial instrument and product markets. The combination of these could give a better idea of how investors process information, and so given the information environment, allow us to make richer empirical predictions about asset prices.

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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 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	390.0	1470.0	917.16	290.94	888.00
Number of customer in the sample per year	208.0	650.0	432.45	115.98	410.50
Full sample % coverage of stock universe (EW)	13.2	31.3	20.25	5.02	19.76
Full sample % coverage of stock universe (VW)	29.1	70.7	50.62	11.83	48.31
Firm % coverage of stock universe (EW)	8.5	22.8	12.79	4.03	13.14
Firm % coverage of stock universe (VW)	3.28	20.0	9.03	4.49	9.15
Customer % coverage of stock universe (EW)	4.9	11.5	7.56	1.77	7.37
Customer % coverage of stock universe (VW)	26.34	66.42	46.44	11.27	43.50
% of firm-customer in the same industry	20.6	27.22	22.91	1.85	22.64
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

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. *MOM* 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 returns minus the CRSP value weighted market return. We assign each CRSP stock to one of 48 industry portfolio at the end of June of each year based on its four-digit SIC code.

Panel A: correlation coefficients							
	CXRET	XRET	MOM	SIZE	B/M	IXRET	CXIRET
CXRET	1.000	0.115	0.008	-0.004	0.008	0.210	0.288
RET		1.000	-0.010	-0.037	0.029	0.162	0.259
MOM			1.000	0.162	0.030	0.002	0.016
SIZE				1.000	-0.226	0.000	0.039
B/M					1.000	0.015	0.028
IXRET						1.000	0.320
							1.000
Panel B: Spearman Rank correlation							
	CXRET	XRET	MOM	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
MOM			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 and Carhart (1997) momentum 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
xret	-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]
Panel A: equal weights						
xret	-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]

Table IV: Customer Momentum portfolio, factor loadings 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 and Carhart (1997) momentum 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.

Factor loadings (Value weights)							
	xret	alpha	mkt	smb	hml	pry1	R^2
Q1 (low)	-0.596	**-0.821**	**0.989**	**0.384**	**-0.318**	**-0.235**	0.626
	[-1.42]	[-2.93]	[14.31]	[4.47]	[-3.10]	[-3.88]	
Q2	-0.157	**-0.741**	**1.057**	**0.307**	-0.115	-0.022	0.658
	[-0.41]	[-3.28]	[17.57]	[4.10]	[-1.28]	[-0.42]	
Q3	0.125	-0.488	**1.063**	**0.309**	-0.09	-0.029	0.633
	[0.32]	[-1.89]	[16.81]	[3.92]	[-0.96]	[-0.52]	
Q4	0.313	-0.193	**1.039**	**0.217**	-0.15	-0.076	0.564
	[0.79]	[-0.72]	[14.43]	[2.42]	[-1.40]	[-1.20]	
Q5 (high)	**0.982**	**0.556**	**0.982**	**0.681**	**-0.363**	-0.056	0.650
	[2.14]	[1.99]	[13.80]	[7.69]	[-3.43]	[-0.90]	
L/S	**1.578**	**1.376**	-0.007	0.296	-0.045	0.179	0.041
	[3.79]	[3.13]	[-0.07]	[1.26]	[-0.28]	[1.93]	

Table V: Under-reaction coefficients

This table shows returns on the customer momentum portfolio and the corresponding under-reaction 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 a 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 under-reaction coefficients. URC (Under-reaction 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 under-reaction. 5% statistical significance is indicated in bold.

	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: Under-reaction 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 VI: 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 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 overlapping portfolios are rebalanced every calendar month to maintain value (equal) weights. We report excess returns of a value (VW) and equally weighed (EW) zero-cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer return stocks. "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 are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold.

	1 month customer return					1 year customer return	
				Skip a week		Skip a month	
	# months	VW	EW	VW	EW	VW	EW
		1	**2**	**3**	**4**	5	**6**
xret	288	**1.578**	**1.311**	**1.464**	**0.932**	0.694	**1.13**
		[3.79]	[4.93]	[3.55]	[3.28]	[1.85]	[4.16]
DGTW	288	**1.121**	**0.839**	**1.061**	**0.634**	0.616	**0.737**
		[3.23]	[3.23]	[3.05]	[2.53]	[1.78]	[2.90]
Smaller firms	288	**1.487**	**1.071**	**1.266**	**0.879**	**1.093**	**1.216**
		[3.95]	[3.06]	[3.69]	[2.45]	[3.13]	[3.66]
Larger firms	288	**1.475**	**1.336**	**1.375**	**1.243**	0.524	**0.987**
		[3.70]	[4.21]	[3.29]	[3.87]	[1.41]	[3.19]
1981 – 1992	144	**1.963**	**1.391**	**1.763**	**0.943**	0.237	**1.137**
		[4.39]	[4.28]	[4.08]	[2.95]	[0.67]	[3.63]
1993 - 2004	144	**1.266**	0.698	1.161	**0.871**	1.081	**1.153**
		[1.99]	[1.66]	[1.72]	[1.96]	[1.77]	[2.75]
Industry adjusted	288	**0.975**	**0.508**	**0.882**	**0.529**	0.50	**0.698**
		[2.89]	[2.14]	[2.55]	[2.25]	[1.41]	[3.24]
Different industry	288	**1.157**	**1.162**	**1.023**	**0.883**	**0.817**	**0.945**
		[4.83]	[2.84]	[3.43]	[3.01]	[2.03]	[3.97]
Same industry	288	**1.288**	**1.192**	**1.173**	**0.901**	0.705	0.349
		[2.49]	[2.90]	[2.34]	[2.90]	[1.42]	[0.90]

Table VII: Cross sectional regressions

This table reports Fama-MacBeth forecasting regressions of individual stocks 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*), and lag return of the corresponding customer industry portfolio (*cindret*). Cross sectional regressions are run every calendar month and the estimates are weighted by the cross sectional statistical precision, defined as the inverse of the standard error the coefficients in the cross sectional regressions. Cross sectional standard errors are adjusted for heteroskedasticity. Fama MacBeth t-statistics are reported below the coefficient estimates and 5% statistical significance is indicated in bold.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
$cret_{t-1}$	**0.043**	**0.042**	**0.042**	**0.035**	**0.037**	**0.037**	**0.023**	**0.026**
	[4.96]	[4.88]	[5.15]	[3.41]	[3.82]	[3.84]	[2.30]	[2.64]
$cret_{t-12,t-2}$		**0.011**	**0.010**		**0.010**	**0.010**		**0.009**
		[4.68]	[4.54]		[3.62]	[3.61]		[2.74]
ret_{t-1}			**-0.018**			**-0.018**		**-0.021**
			[-2.96]			[-2.92]		[-3.26]
$ret_{t-12,t-2}$						**0.004**		**0.004**
						[2.14]		[2.13]
$indret_{t-1}$				**0.105**	**0.091**	**0.098**	**0.071**	**0.067**
				[3.44]	[3.06]	[3.40]	[2.42]	[2.40]
$indret_{t-12,t-1}$					0.011	0.011		0.008
					[1.83]	[1.76]		[1.40]
$cindret_{t-1}$							**0.213**	**0.208**
							[6.01]	[6.20]
$cindret_{t-12,t-1}$								-0.008
								[-1.27]
R^2	0.010	0.013	0.028	0.017	0.023	0.037	0.022	0.042

Table VIII: 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 stocks return. The explanatory variables are the lagged customer returns (*cret*), the stock's own lagged return (*ret*), lagged return of the corresponding industry portfolio (*indret*), and lag return of the corresponding customer industry portfolio (*cindret*). 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 EW or value weighted VW). 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.

	EW					*VW*				
$cret_{t-1}$	**0.895**	**0.691**	**0.730**	**0.724**	0.445	**1.170**	**0.906**	**1.151**	**1.178**	**0.855**
	[4.03]	[2.59]	[2.99]	[3.01]	[1.83]	[3.57]	[2.44]	[3.10]	[3.26]	[2.26]
$cret_{t-12,t-2}$	**0.529**		**0.598**	**0.604**	**0.529**	-0.136		-0.029	-0.043	-0.102
	[2.88]		[2.80]	[2.83]	[2.44]	[-0.43]		[-0.08]	[-0.12]	[-0.29]
ret_{t-1}	**-0.862**			**-0.866**	**-1.005**	-0.119			0.026	-0.079
	[-2.69]			[-2.69]	[-3.22]	[-0.32]			[0.07]	[-0.22]
$ret_{t-12,t-2}$				0.167	0.194				0.373	0.283
				[0.53]	[0.62]				[0.86]	[0.66]
$indret_{t-1}$		**1.013**	**0.791**	**0.819**	**0.518**		0.563	0.297	0.243	0.098
		[3.51]	[3.04]	[3.32]	[2.33]		[1.52]	[0.87]	[0.74]	[0.30]
$indret_{t-12,t-1}$			0.208	0.219	0.180			-0.286	-0.271	-0.280
			[0.92]	[0.97]	[0.85]			[-0.79]	[-0.73]	[-0.80]
$cindret_{t-1}$					**1.407**					**1.096**
					[4.92]					[3.35]
$cindret_{t-12,t-1}$					-0.380					0.202
					[-1.79]					[0.62]

Table IX: Variation in inattention: mutual fund holdings

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 at the end of the previous month. The ranked stocks are assigned to one of 5 quintile portfolios. Stocks are further independently ranked in three groups, bottom 30% (P1), mid 40% (P2), top 30% (P3) based on COMMON, which is measured as the number of mutual funds holdings both customer and supplier in their portfolio in that calendar month. 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 excess returns of a value (VW) and equally weighed (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.

	COMMON	
	VW	EW
P1	**3.032**	2.057
(Low COMMON)	[2.70]	[1.95]
P2	1.314	0.469
	[1.30]	[0.57]
P3	0.554	0.335
(High COMMON)	[0.58]	[0.46]
P3 minus P1	**-2.479**	-1.722
	[-1.98]	[-1.44]

Table X: 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 year 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^{Sup}, OI^{Cus})	**0.077** [3.88]	38.7%
OI_L^{Cus}	0.275	0.358	OI_{NL}^{Cus}	0.199	0.222	(S^{Sup}, S^{Cus})	**0.145** [8.55]	51.4%
S_L^{Cus}	0.315	0.428	S_{NL}^{Cus}	0.237	0.283			

Table X: 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-1)	**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

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).

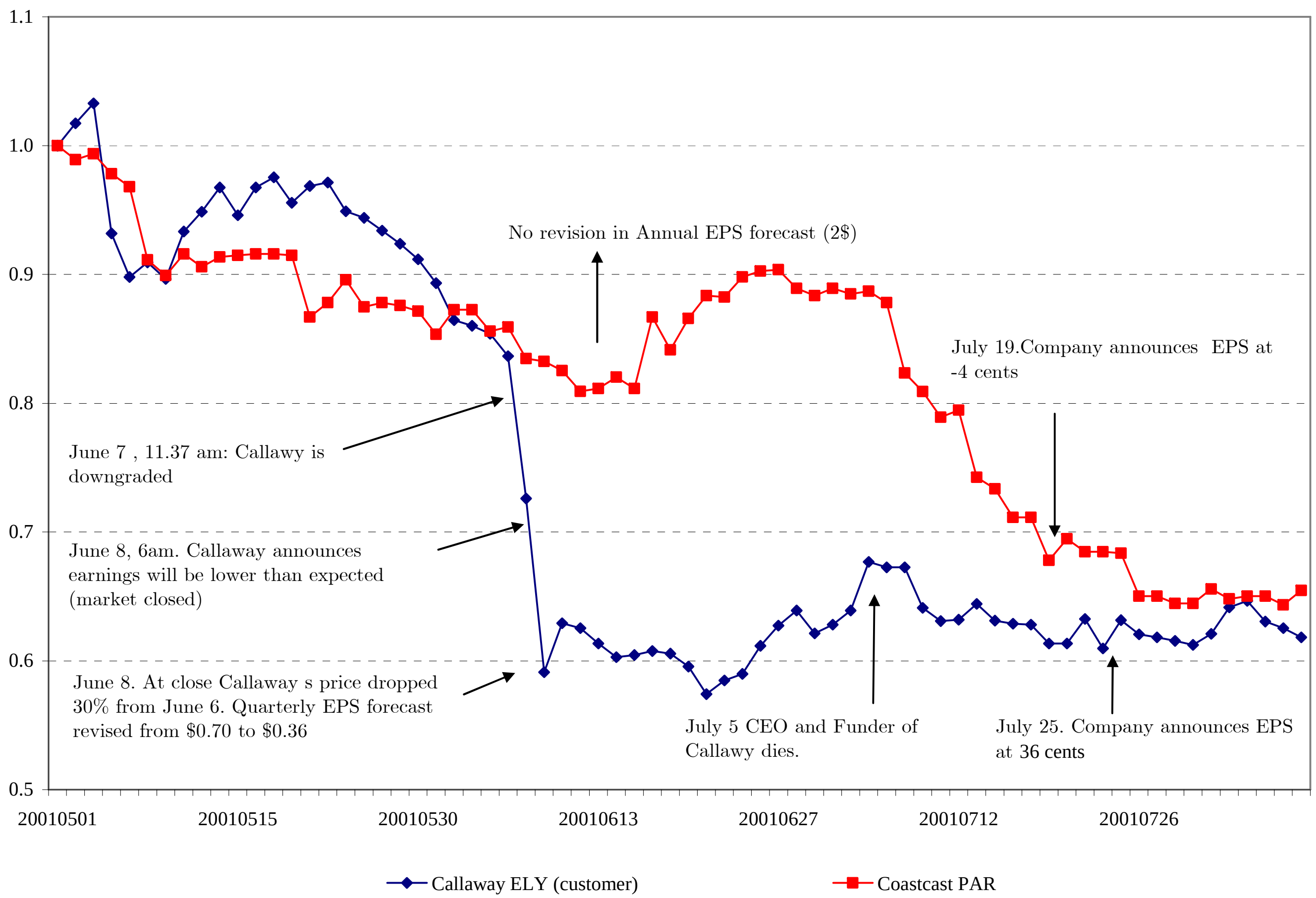

Figure 2: Size distribution

This figure plots the distribution of market capitalization of the customer/supplier sample. Every calendar month we assign socks to size deciles using NYSE breakpoint. We plot the % of stocks in each size bin. This figure includes all available stocks with price greater than 5$ between 1981 and 2004.

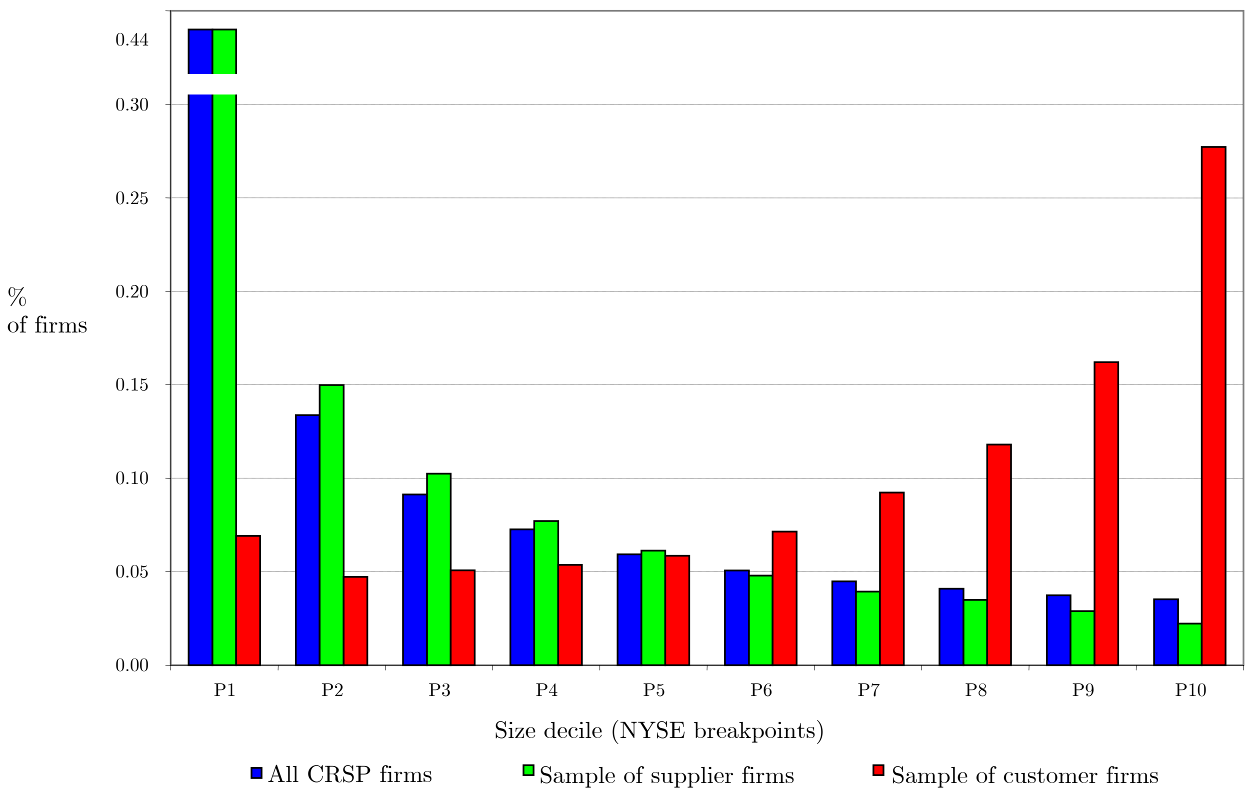

Figure 3: Customer momentum, event-time CAR

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

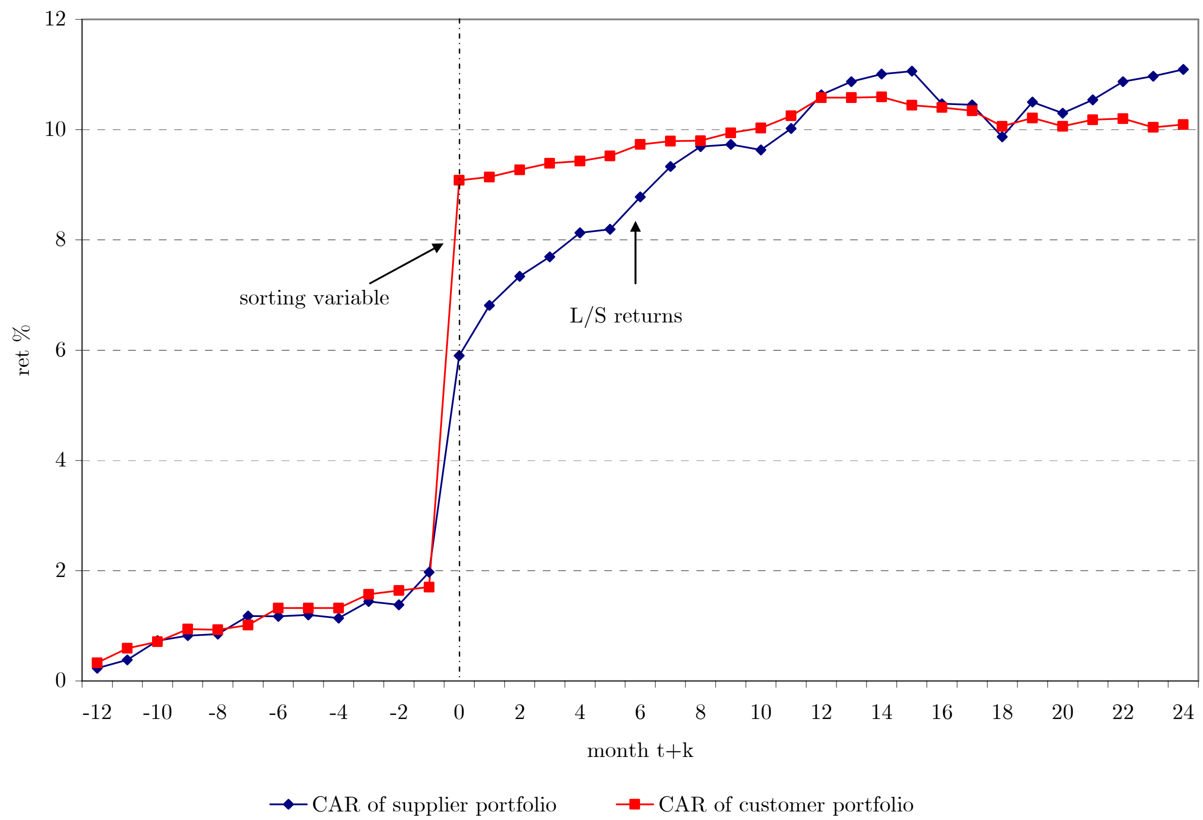

Figure 4: Annual returns of customer momentum strategy

This figure shows annual buy-and-hold returns on a long/short portfolios formed on 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 comprised of its major customers in at the end of the previous month. Stocks are assigned to one of five quintile portfolios. Portfolios are rebalanced monthly to maintain value weights. The figure shows annual returns of a zero cost portfolio that holds the top 20% high customer return stocks and sells short the bottom 20% low customer returns stocks