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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. Using a data set of firms' principal customers to identify a set of economically related firms, we 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.

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

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[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.

related firms will have a predictable lag in reacting 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.

Two conditions need to be met to test for investor limited attention: (i) any information thought to be overlooked by investors needs to be available to the investing public before prices evolve, and (ii) the information needs to be salient information that investors should be reasonably expected to gather.

While 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 shareholders. Regulation SFAS No. 131 requires firms to report the identity of customers representing more than 10% of their total sales in interim financial reports issued to shareholders. In our linked sample, the average customer accounts for 20% of the sales of the supplier firm. Therefore, customers represent substantive stakeholders in the supplier firms. Furthermore, in some cases, the customer–supplier links are longstanding relationships with well-defined contractual ties. Second, and more importantly, because we examine material customer–supplier links, the link is in fact salient information when forming expectations about future cash flows and in turn 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 first group stocks into different classes for which news about linked firms has been released into the market. We then 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 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 that specialized in golf equipment.[2] As of 2001, Callaway accounted for 50% of Coastcast's total sales. On June 7, 2001, Callaway was downgraded by one of the analysts covering it. In a press release on June 8 Callaway lowered second-quarter revenue projections to $250 million, down from a previous projection of $300 million. The announcement brought Callaway's 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" recommendations dropped from 77% to 50%, and going forward, nearly 2 months later, when

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

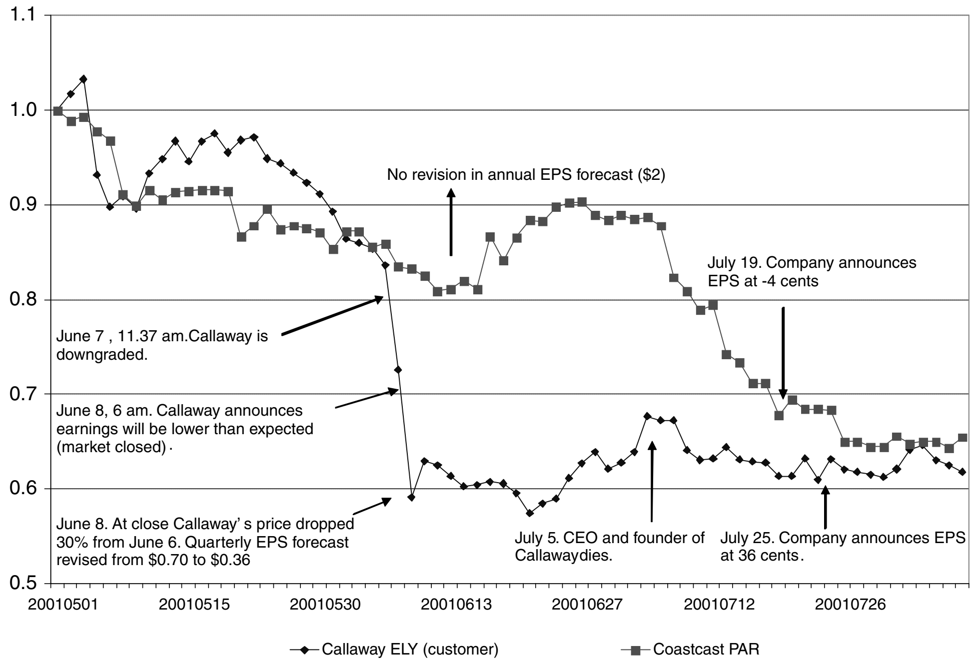

Figure 1. Coastcast Corporation and Callaway Golf Corporation. This figure plots the stock prices of Coastcast Corporation (ticker = PAR) and Callaway Golf Corporation (ticker = ELY) between May and August 2001. Prices are normalized (05/01/2001 = 1).

Callaway announced earnings on July 25, it hit the revised mean analyst estimate exactly with 36 cents per share.

Surprisingly, the negative news in early June about Callaway's future earnings did not impact Coastcast's share price at all, despite the fact that the customer accounting for half of Coastcast's total sales lost 30% of market value in two days. Both EPS forecasts ($2) and stock recommendations (100% buy) were not revised. Furthermore, a Factiva search of newswires and financial publications returned no news mentions for Coastcast at all during the 2-month period subsequent to Callaway's announcement. Ultimately, Coastcast announced EPS at –4 cents on July 19 and experienced negative returns over the subsequent 2 months.

In this example, we are 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 2 months after Callaway's announcement 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 2 months.

The above example represents a pattern that is systematic across the universe of U.S. common stocks: Consistent with investors' inattention to company links, there are significantly predictable returns across customer–supplier 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, 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 the case that unrelated to investor's limited attention to 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 the customer's return is simply a noisy proxy for the supplier's own past return. 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 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 the extent of inattention varies the magnitude and significance of the result. We use mutual funds' joint holdings of customer and supplier firms to identify a subset of firms where investors are a priori more likely to collect information on both the customer and supplier, and hence to be attentive to the customer–supplier link. For all mutual funds that own the supplier firm, we determine the percent that own both the customer and the supplier (common) and the percent that own only the supplier (noncommon). 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 noncommon managers trade the supplier only with a significant (one 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 nonlinked years. We then show that when two given firms are linked, customer shocks today have significant predictability over the supplier's future real activities, while when they are not linked, there is no predictive relationship. Also, the sensitivity of suppliers' future returns to customer shocks today doubles when customers and suppliers are linked as opposed to not linked.

The remainder of the paper is organized as follows. Section I briefly provides a background and a 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 the rerelease of information in the *New York Times* that had been published in *Nature* 5 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 and 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 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)

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

finds evidence that such lead-lag effects are predominantly an intraindustry 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 (e.g., 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 postearnings 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, while Hirshleifer et al. (2004) find long-run return evidence consistent with investors focusing on accounting profitability while displaying inattention toward cash profitability. 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 et al. (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 consistent with our own results, that individual customer returns 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. Rather, we focus on what we believe from the investors' standpoint may be the more intuitive links of customer–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 allow 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 are 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 nonmissing values 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 were 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 we then hand-match the customer to the corresponding permno number by inspecting the firm's name, segment, 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 6-month gap between fiscal year-end dates and stock 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. In contrast, the distribution of our sample of firms' principal customers is tilted toward large cap securities: The average customer size is above the 90$^{\text{th}}$ size percentile of CRSP firms. This difference partially reflects the data generating

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

[5] CRSP share codes 10 and 11.

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

[7] We use a "soundex" algorithm to generate a list of potential matches.

[8] See, for example, Fama and French (1993).

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 the Compustat book value of equity. Size is the firm's market value of equity.

	Min	Max	Mean	*SD*	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
Percentage of sales to customer	0.00	100	19.80	17.05	14.68

process. Firms are required to disclose the identity of any customer representing more than 10% of 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.

On average the universe of stocks 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.

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

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. In particular, stock prices underreact to negative (positive) news involving related firms, and in turn generate negative (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 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.

[10] Using different weighting schemes to compute customer returns does not affect the results. We replicate all our results using customer returns computed by setting weights equal to the percentage of total sales going to each customer. For most of the paper, we choose 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.

The time series of these portfolios' returns 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 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 the customer–supplier link into account when forming and updating prices, in principle there is no reason to restrict the analysis to a customer momentum strategy. The current financial regulation, however, 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.

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 our test portfolios' abnormal returns after hedging out inter- and intra-industry exposure.

[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

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

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 12 months. Size is the log of market capitalization as of the end of the previous calendar month. *B/M* is the book-to-market ratio, which is the market value of equity divided by the 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 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% high customer return stocks and sells short the bottom 20% low customer return stocks. To be included in the portfolio, a firm must have a nonmissing customer return and nonmissing 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 microcapitalization 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 returns today predict 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), or 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 five-factor model by adding

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

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 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. 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, the Carhart (1997) momentum factor, and the 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 by *.

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]
Three-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]
Four-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]
Five-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]
Three-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]
Four-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]
Five-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]

the traded liquidity factor of 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-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.

[14] The traded liquidity factor is obtained by sorting the CRSP monthly stocks file data into 10 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.

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

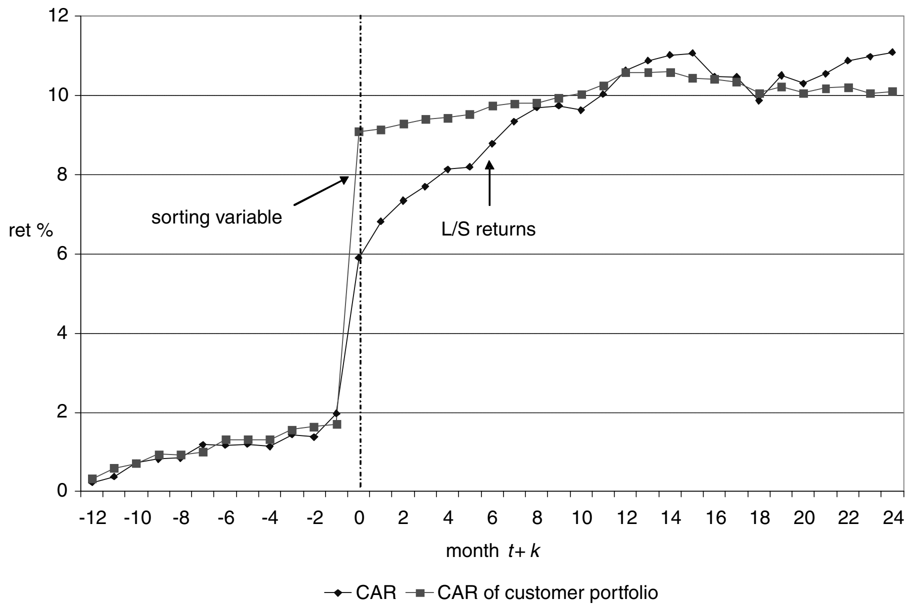

Figure 2. Customer momentum, event-time CAR. This figure shows the average cumulative return in month $t+k$ on a long–short portfolio formed on the firm's customer return in month t. At the beginning of every calendar month, stocks are ranked in ascending order based on the return of a portfolio of its 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.

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).

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

[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 underperforms the market. The three-factor monthly alpha of an equally weighted portfolio of all suppliers in our sample is −41 basis points, probably due to the fact that U.S. suppliers have been continuously squeezed by international competition (we thank Tuomo Vuolteenaho for suggesting this interpretation).

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% over the subsequent year. The predictable positive returns persist for about a year and then fade away.

In Table IV we explore the relation between the customer returns, the initial stock price reaction of related firms, and the subsequent price drift on both the customer and supplier. We compute customer returns using weights equal to the percentage 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, and *CCAR* is the customer cumulative return over the subsequent 6 months. Similarly, *RET* is the supplier stock return in month t, and *CAR* is its cumulative return over the subsequent 6 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]

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 6 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 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

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

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 $5 at portfolio formation. Panel A reports the average cumulative returns on long–short portfolios formed on the firm customer return in month t. *CRET* is the customer return in month t. *CCAR* is the customer cumulative returns over the subsequent 6 months [t+1, t+6]. *RET* is the supplier's stock return in month t. *CAR* is the cumulative return over the subsequent 6 months. t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated by *. Panel B reports the underreaction coefficients. *URC* (underreaction coefficient) is defined as the fraction of total returns from month t to month t+6 that occurs in month t ($URC = RET/(RET + CAR)$). *PERCSALE* is the % of firm 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 one, which is the case of no underreaction. 5% statistical significance is indicated by $*$.

	All Firms	Larger Firms	Smaller Firms	PERCSALES Quintiles 1(Low)	2	3	4	5(High)	5-1
				Panel A: Supplier and Customer Returns					
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]

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 6 months. Smaller firms cover only 35% of the gap in the initial month, closing the remaining 65% in the subsequent 6 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 in 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 in which, at portfolio formation, customer firms are larger, have higher turnover, have a higher number of analysts providing earnings estimates, and finally have higher institutional ownership than supplier firms.[19]

[18] Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), 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 institutions 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.

Table V

Robustness Tests

This table shows calendar-time portfolio 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 in the previous month. The ranked stocks are assigned to one of five 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, the Carhart (1997) momentum factor, and the 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 1-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 by *.

Panel A: Value-Weighted Returns, 1981–2004						
	Five-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]

(continued)

Table V—*Continued*

Panel B: L/S Returns

		1-Month Customer Return						1-Year Customer Return Skip a Month	
				Liquid Stocks		Skip a Week			
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]

These filters reduce the sample considerably, given that SFAS 131 requires that firms 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 supplier firms that are larger than their customers, the average monthly five-factor alpha across all four 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 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. The results in Table V show this adjustment has little effect on the return of the customer momentum portfolio. Given the evidence on five-factor alphas in Table III and the results of Table V, we conclude that liquidity is unlikely to be driving the customer momentum result.

Daniel and Titman (1997, 1998) suggest that characteristics can be better predictors of future returns than factor loadings. Following Daniel et al. (1997), we subtract from each stock return the return on a portfolio of firms matched on market equity, market-to-book, and prior 1-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 V show that firms whose customers experienced good (bad) news out- (under-)perform their corresponding characteristic portfolios or industry benchmark. Splitting the sample

[20] Lo and MacKinlay (1990).

[21] These 125 portfolios are reformed every month based on the market equity, market-to-book 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.

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 also has little effect on the results.

Columns 7 and 8 report results for a portfolio sorted on 1-year customer returns. We skip a month between the sorting period and portfolio formation. Looking at 1-year customer momentum, the results do vary by firms' size. For equally weighted portfolios (or for smaller firms) the 1-year customer momentum is large and highly significant. The baseline 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 1-year customer momentum is about 70 basis points 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. Because we are interested in testing return predictability of individual stocks generated by firm-specific news about linked firms, 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 1-month and 1-year lagged stock returns of the firm's principal customer. We include as controls the supplier firm's own 1-month lagged stock return and 1-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 customers' 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 the 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 1-month-ahead forecasting regressions, the time series of the regression coefficients can be interpreted as the monthly return of a 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, and hence the regression could call for extreme overweighting of some securities. To obtain feasible returns, we follow Daniel and Titman (2006) and 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 four-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, 1-month reversals, price momentum, industry momentum, cross-industry momentum, and lead-lag effects.

The results in Table VI give an unambiguous answer: Past customer returns forecast subsequent supplier stock returns. The effect is large, robust, and largely 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 of the 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 as *COMOWN* = (*#COMMON*/*#FUNDS*), that is, 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*

[23] For brevity we only report coefficients on the small and large industry portfolios.

[24] See Fama (1976).

[25] See Daniel and Titman (2006).

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

Table VI

Cross-Sectional Regressions, Hedged Returns

This table reports monthly abnormal returns of a 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*), the lagged return of the corresponding industry portfolio (*INDRET*), the lagged return of the corresponding customer industry portfolio (CINDRET), the lagged returns of the corresponding size-sorted small (*P1_IRET*) and large (*P3_IRET*) industry portfolio, and the lagged returns of the corresponding customer size-sorted small (*P1_CIRET*) and large (*P3_CIRET*) industry portfolio. To compute size-sorted portfolios 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. Firm size (log of market equity), book-to-market, 1-month size-sorted medium (P2) industry and customer industry portfolios, and 1-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 the Carhart (1997) momentum factor. Returns are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated by *.

	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]
$\mathrm{CRET}_{t-12,t-2}$	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]
$\mathrm{RET}_{t-12,t-2}$	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]	
$\mathrm{INDRET}_{t-12,t-1}$		0.208	0.219	0.18			−0.286	−0.271	−0.28	
		[0.92]	[0.97]	[0.85]			[−0.79]	[−0.73]	[−0.80]	
$\mathrm{CINDRET}_{t-1}$				1.407*					1.096*	
				[4.92]					[3.35]	

	Equal Weights					Value Weights				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$CINDRET_{t-12,t-1}$				−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]

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 into prices more quickly for stocks with a higher fraction of common fund ownership.

Every calendar month, we use independent sorts to rank stocks in two groups (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 the 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 (those 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 VII show this same pattern: Prices of suppliers with a lower fraction of managers holding shares of both the customer and the supplier underreact significantly more to news about related customers than suppliers who are more 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, in some subsamples we are unable to reject the null hypothesis that the returns are statistically different.[28]

[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.

Table VII
Mutual Fund Common Ownership, Customer Momentum Returns

This table shows calendar-time portfolio 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 in the previous month. The ranked stocks are assigned to one of five quintile portfolios. The portfolios 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 by $*$.

			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)	
	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 percentage 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 percentage 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]

The results in Table VII lend support to the customer momentum returns 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 appears to be impounded into prices more quickly for stocks with a higher fraction of *COMOWN*.

As common holding managers are more likely to jointly monitor both the customer and the 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, and thus 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 (noncommon 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

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

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 noncommon managers (NC). We regress net purchases in quarter t on contemporaneous and lagged customer returns (CRET), and a series of controls $\mathbf{X}$,[30] to estimate the sensitivity to linked customer news:

$$NETBUY^{i}_{t} = a + b^{i}_{1}CRET^{i}_{t} + \theta^{i}\mathbf{X}^{i}_{t} + \upsilon^{i}_{t} \qquad i \in \{C, NC\}. \tag{2}$$

Under the null hypothesis that common managers are more likely to trade stocks in response to news about related firms we have $b^{C}_{1} > b^{NC}_{2}$. 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 the case that common managers react to shocks about

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

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

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 the semiannual or at most the quarterly level, we cannot distinguish between the two hypotheses. We simply test the hypothesis that, when compared to noncommon 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 and 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] The results in Table VIII show that common managers are more likely to be net purchasers (sellers) of stocks in quarters in which their customer firms experience large positive (negative) returns, while noncommon 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 noncommon 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] 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 noncommon managers show almost zero net trading. Net purchases by noncommon managers spike 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 (one quarter).

Models 2 and 3 in Table VIII show that, controlling for the firm's own past returns, noncommon managers' net purchases are unrelated to both contemporaneous and lagged customer returns, while they are strongly related to the firm's own stock return. Thus, given a customer shock at date t, it appears that noncommon manager net purchases at date $t+1$ are entirely due to the fact

[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 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.

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 in 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 in 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 lagged customer return ($CRET$), the stock's own contemporaneous and lagged returns (RET), the return of the corresponding industry portfolio ($INDRET$), the stock's market capitalization (ME), and the book-to-market ratio (BM).

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

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 by *.

	(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	

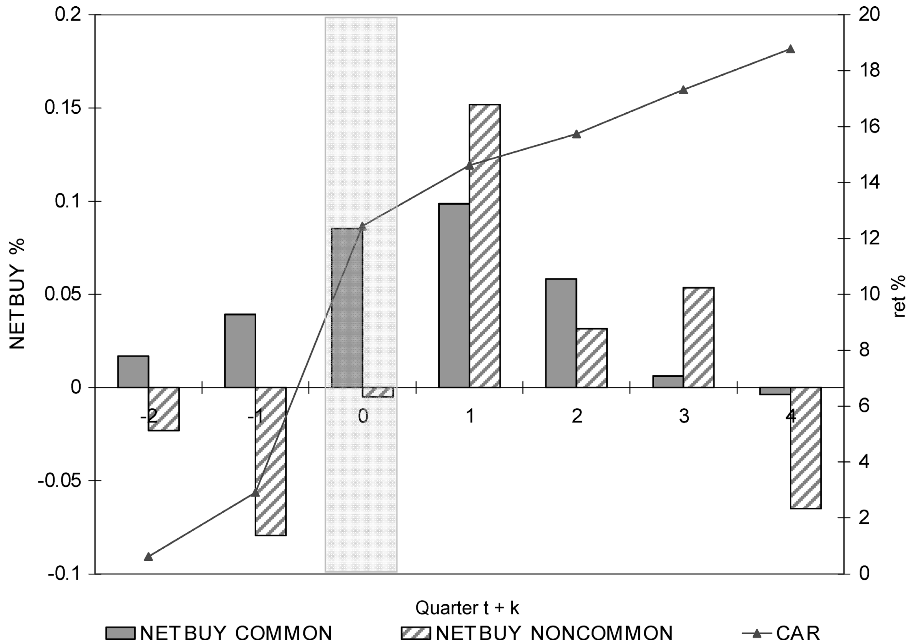

Figure 3. Customer momentum, event-time CAR, and mutual fund's net purchases. This figure shows the average cumulative return and mutual funds net purchases in quarter $t+k$ on a long-short portfolio formed on the firm's customer return in quarter t. At the beginning of every quarter, stocks are ranked 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 noncommon funds. For a given stock *NETBUY COMMON* is defined as $\Delta CS_t / SHROUT_{t-1}$, where ΔCS_t is the change in 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 NONCOMMON* is defined as $\Delta NCS_t / SHROUT_{t-1}$, where ΔNCS_t is the change in total number of shares owned by mutual fund managers that do not hold the customer in their portfolio.

that 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 a supplier's own returns, the marginal effect of customer returns on noncommon managers' net purchases is not significant.

Taken jointly, the results in Tables VII and VIII, and in Figure 3, 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 linked customers, thus reducing "inattention" to the customer–supplier link, see 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 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 a customer and a 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 one when two firms are linked via a customer–supplier relationship, 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 suppliers' subsequent profits and returns within a given industry-pair (e.g., steel and automobiles) and year (e.g., 1981), solely because the given set of firms are linked as opposed to not linked.

The results in Column 1 and Column 2 of Panel C suggest that when a customer and supplier are not linked, shocks to the customer do not have predictive power over the future profits or sales of the supplier. In contrast, when the two firms are linked ($LINK * CRET$), customer shocks today predict the future real shocks in the supplier firm. 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 via a customer–supplier relationship than when they are not linked. This lends support to the assumption, and affirms the intuition, that customer–supplier relationships generate significant comovements in the underlying cash flows of the linked firms, and thus should be given attention by investors.

[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.

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 1-year lagged 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). Nonlink year is a year when the customer and supplier are not linked in the data. Panel B reports differences between link and nonlink 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% 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 by *.

OI_L^{Sup} = Operating Income of Supplier/Assets Linked S_L^{Cus} = Sales of Customer Linked

$_l OI_{NL}^{Sup}$ = 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*	38.7%
							[3.88]	
S_L^{Cus}	0.315	0.428	S_{NL}^{Cus}	0.237	0.283	(S^{Sup}, S^{Cus})	0.145*	51.4%
							[8.55]	

(continued)

Table IX—*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

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, and this limited attention having a substantial effect on asset prices. The customer–supplier links in the paper are publicly available and in some cases represent 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 (selling) the supplier firm following a positive (negative) shock to its customer. This customer momentum strategy yields large returns and is largely unaffected in both magnitude and significance by controlling for the three-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 intradaily 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 that is constrained to a few firms, but instead is a systematic violation across firms that has a material effect on prices. If it is true that investors ignore even these blatant links, then the informational efficiency of prices to reflect more complex pieces of information is potentially less likely. We believe 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.

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