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Two Essays on Investors' Attention to Economically Linked Firms

Mahsa Khoshnoud
University of Central Florida

TWO ESSAYS ON INVESTORS' ATTENTION TO ECONOMICALLY LINKED FIRMS

by

MAHSA KHOSHNOUD

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ABSTRACT

My first essay examines the degree to which the market prices of publicly traded firms reflect and respond to new information regarding the economic viability and vitality of organizations to which they are strategically linked. More specifically, I exploit the uniquely transparent nature of the lessor-lessee relationship across commercial real estate markets to evaluate whether future returns to real estate investment trusts (REITs) are systematically affected by the financial return performance and/or operational opacity of the tenants who lease their investment properties. Using a hand collected data set identifying the principal tenants of 96 publicly traded REITs, I find those firms with the best performing tenants generate annualized abnormal returns which are approximately six percent higher than those realized by REITs with the worst performing tenants. These results are robust to a variety of model specifications, and a closer inspection of the results reveals these performance differentials are consistent with emerging evidence across the literature suggesting investors' limited attention materially influences the return predictability of assets. With respect to the current investigation, I thus conclude investors' limited attention leads to the failure of REIT prices to fully reflect the valuation implications of their tenants' return performance.

My second essay investigates how sophisticated investors, such as short sellers, trade on information along the supply chain. Short sellers are known to be generally better informed than common investors. Given the economic linkages that exist between the suppliers and customers, one would expect short sellers to trade on such information. My results indicate that short interest predicts unexpected earnings news, consistent with short sellers extracting information from economic relationships. When I evaluate stock return and short interests in regression analysis, I find strong negative relation between short interest in supplier firm and the future stock returns for the customer firm for the return in the next month. The negative relation persists for twelve months. I find similar results from portfolio approach. I argue that one plausible channel that explains the information content of supplier (customer) firm’s short interest for the customer (supplier) firms is short sale constraints on the customer (supplier) firms. My results are consistent with this explanation. Overall, my findings suggest that short sellers play an important role in the price discovery of related firms on supply chain, beyond their direct effects documented previously.

For Pari & Ahmad.

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TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

ESSAY1: INVESTORS' LIMITED ATTENTION: EVIDENCE FROM REITS

1. Introduction

Market efficiency implies that any new information regarding an asset is fully reflected and instantaneously incorporated into its current market value. In practice, such asset market efficiency requires investors to both: 1) provide full attention to all available information regarding a firm, and 2) continuously incorporate new information into their investment decision making. For example, one potentially important source of information regarding future firm returns is the financial performance of other firms to which it is economically linked. Interestingly, however, Cohen and Frazzini (2008) find investors are often inattentive to the full implications of such relations, and further argue such inattention may result in systematic return predictability across related assets. Their evidence is also consistent with models of limited attention and gradual information flow, where attention constraints cause related firm information to diffuse slowly across investors, thereby generating predictable returns (Hong and Stein 1999; Hirshleifer et al. 2009; Hirshleifer et al. 2011).

Building upon these foundations, the current investigation explores the valuation consequences of investor limited attention in real estate markets. More specifically, exploiting the unique transparency of the tenant-landlord relationship in commercial real estate markets, I evaluate the extent to which performance information regarding an income producing property's tenants affects the future returns of their landlords. Throughout this analysis, I focus on real estate investment trusts (REITs) and the markets in which they operate. REIT markets provide an appropriate setting and compelling laboratory for testing investors' attention for multiple reasons.

First, information regarding the tenants of REIT owned properties, as well as information about the financial performance of those tenants, is frequently available to the public on a timely basis. For example, the SNL financial data base reports the top tenants for each REIT in its coverage universe, including detailed information on the geographic scope and exposure of each tenant. In addition, this public information is typically very transparent, and relatively easy to access. Additionally, the economic link between REITs and their tenants is traditionally contractual in nature, with REIT income derived from tenant rent collection. As such, the economic link between tenant and REIT performance should be readily apparent, with new information along this dimension likely serving as a critical and value-relevant dimension of a REIT's market valuation. Finally, as outlined by Capozza and Lee (1995), REITs may well be valued with much greater certainty than their Non-REIT counterparts within real estate markets, as the securitized nature of their equity shares facilitates enhanced liquidity, which should in turn improve the efficiency of the price discovery process.

All of the attributes discussed above suggest the potential influence of limited investor attention on firm valuation should be less pronounced within publicly traded REIT markets. As such, I contend that to the extent investors fully consider key economic linkages, the market prices of REITs will quickly and correspondingly respond to positive or negative performance shocks to their core tenants. On the other hand, if investors ignore these potentially important and transparent relations, REIT stock prices will evidence a lagged adjustment, as profitability fundamentals are only slowly recognized and incorporated into realized cash flows. In other words, given limited investor attention, the market prices of REITs will be predictable based upon the previous returns of their core tenants. Previewing my focal empirical results, I find the financial (return) performance of commercial property tenants strongly predicts the future returns of the REITs which own their facilities (i.e., their landlords). More specifically, the monthly strategy of buying REITs whose tenants had the most positive returns (top tercile) in the previous month, and selling short REITs whose tenants had the most negative returns (bottom tercile), yields abnormal returns of approximately 0.40 - 0.50% per month, or 5% to 6% per year. I refer to this return predictability as "tenant momentum," and view my results as strong evidence that information transmission regarding the REIT-Tenant relation is only slowly recognized by investors. As such, I conclude REIT markets may well be characterized by issues related to limited investor attention.

The remainder of the paper is organized as follows. Section II reviews the existing literature to provide insight into the predictions and valuation implications of the limited investor attention hypothesis, and further explores why these issues may be of central importance to REIT investors. Section III describes the data and methodological approaches employed throughout my empirical analyses to examine these potential relations, while Section IV presents my main empirical results with respect to the return predictability of tenant returns. Section V explores the robustness of these relations, and presents the results of a number of tests examining variation in return predictability across alternative dimensions of investor inattention. Finally, Section VI concludes the paper with a summary of my key findings, along with a discussion of their implications.

2. Previous Literature and Hypothesis Development

Traditional asset pricing models typically assume information is instantaneously incorporated into market prices when it becomes available. The validity of this assumption requires that investors both allocate sufficient attention to the asset, and further, that they consider all available information within the marketplace. In reality, attention is a scarce cognitive resource (Kahneman 1973), and thus, investors have limited attention (Da et al. 2011).

To elaborate, the Limited Attention Hypothesis (LAH) is based on the assumption that investors face both time and processing constraints, which limit their ability to monitor and process multiple types and/or sources of information at any one time. As a result, investors are generally forced to focus on only a subset of available information regarding the firms in which they invest. For example, if an individual focuses on understanding the implications of the financial report of one firm, they may be unable to simultaneously and effectively analyze and assess more complex or nuanced information regarding the non-financial disclosures by that same firm. Alternatively, this focus may lead them to miss important, value-relevant changes in the firm's competitive market dynamics, such as the financial performance and/or operating position of its peers.[1]

To the extent inattentive investors fail to accurately and efficiently incorporate all value relevant information into security prices, return predictability may be observed. Consistent with this notion, Peng et al. (2006) find significant evidence of asset return predictability in the presence of investor inattention, and further, argue such return predictability increases with investor overconfidence. In related work, Huang and Liu (2007) develop a theoretical model showing rational inattention alters the optimal trading strategy, resulting in potential (under-) over-

[1] An emerging literature finds evidence of such investor under reaction to firm specific information, including information regarding related firms. Of note, Ramnath (2002) is among the first to empirically examine such issues, and finds evidence consistent with investor under reaction to the performance of peer firms within the same industry.

investment. Additionally, they demonstrate investors with higher levels of risk aversion, and those with a longer investment horizon, may rationally choose less frequent but more accurate periodic news acquisition. Conversely, exploring this same paradigm, Thomas and Zhang (2008) examine how the stock price of a late announcing firm is affected by the early announcements of its peers. Consistent with an overreaction to these early announcements, the authors find a strong negative correlation between the two prices.

The investor limited attention hypothesis has also been offered as one potential explanation for post-earnings announcement drift (PEAD). For example, Dellavigna and Pollet (2009) find Friday earnings announcements are characterized by both lower trading volume and more drift. Similarly, Hirshleifer et al. (2009) examine investor attention when there are multiple earnings announcements on the same day, and find the reaction to earnings news is significantly less sensitive on high-news days than on low-news days. More formally, Hirshleifer et al. (2011) extend this line of reasoning and develop a model showing that both the average price reaction to an earnings surprise, and the average post-earnings announcement drift, increase along with the magnitude of the earnings surprise. They also document that the percentage of inattentive investors is inversely related to the market's immediate reaction to a given earnings surprise, and directly related to both the degree of misvaluation and the level of post-earnings announcement drift. Taken together, the results of these prior studies suggest investor limited attention exerts a potentially meaningful influence over observable market outcomes.

With respect to the current investigation, I extend this emerging literature (Cohen and Frazini, 2008, etc.) on firms that are economically linked, and contribute to this fast growing body of literature by critically examining the relation between landlords (e.g., REITs) and the tenants who lease their investment properties. As a group, real estate investment trusts generate the bulk of their revenue by owning and/or operating real estate properties. For example, retail REITs typically earn revenue by leasing their properties to retail tenants. Alternatively, they may also operate retail centers owned by third parties. Under such an arrangement, the REIT generally receives a percentage of the center's revenues, called a "management fee," in exchange for their services.[2] Because they lease space to retailers, retail REITs are particularly sensitive to U.S. Economic Cycles. In general, retailers struggle during economic down turns, thus decreasing the demand for retail property space during such times. This issue was brought into sharp relief as the U.S. economy began to slump in 2008. During that year, a number of mid-size retail chains including Sharper Image (SHRP), Linen's and Things, and the furniture store Levitz all declared bankruptcy. Similarly, Foot Locker (FL), Zales (ZLC), and Ann Taylor all announced over 100 store closings, while even off-price retailers such as T.J. Maxx experienced slower sales. Store closures and tenant bankruptcies lower the demand for retail properties, increase vacancy rates, and decrease rent collections. In the aftermath of these events, Liu and Liu (2013) examined the economic link between landlords and tenants by focusing on the stock market responses of REITs to bankruptcy announcements by their major tenants. More specifically, they examined 157 major tenant bankruptcy announcements of retail real estate firms over the period 2000-2010. Consistent with a growth option hypothesis, they found that during good economic times, tenant bankruptcy has a less negative (or more positive) effect on a landlord's stock return. Intuitively, during robust

[2] Retail leases often contain percentage rent clauses designed to align the interests and incentives of landlords with those of their tenants. Such clauses, as with management fees based upon center revenue, further strengthen and underscore the economic relations between REIT landlords and their tenants.

economic periods replacement tenants should be easier to find. To the extent market lease rates have been increasing, replacing a bankrupt tenant may even increase expected firm revenues if it enables the landlord to exit a below market rate contract and effectively mark the replacement rent back to current market levels. Furthermore, they also find owners of properties located in markets with a highly diversified economic base are more likely to exercise the growth option given a tenant departure, and thus realize higher stock returns. Throughout the current paper, Iexpand the unit of analysis to examine the financial return performance of the broad cross-section of commercial real estate tenants and the resulting impact on the stock returns of their (REIT) landlords, not simply those who have filed for bankruptcy protection.

While financial distress may serve as a stark reminder and clear example of how firms are economically linked, I believe the investor limited attention hypothesis (LAH) has widespread, generalizable implications that my broader sample is more appropriately designed to identify and capture. More specifically, it is against this backdrop that I explore the valuation implications and return predictability of the investor limited attention hypothesis within REIT markets, and more specifically investigate the potential for under reaction to firm specific news. To the best of my knowledge, the current manuscript represents the first effort to systematically and rigorously explore the issue of investors' limited attention within the context of real estate, and more specifically REIT, markets. While Price et al. (2010) examine post earnings announcement drift (PEAD) in REITs, they rely on information uncertainty as their primary motivation for the existence and persistence of drift. As such, ex-ante they predict the transparency of REIT assets should result in reduced PEAD for REITs relative to that found for Non-REIT industrial firms. Interestingly, their empirical results find an economically significant drift of nearly 20% (on an annualized basis) for their sample of REITs, which is significantly larger than the 12% (again, on an annualized basis) they find for their Non-REIT observations.

Bridging back to the central theory, when investors process one type of information regarding a set of REITs, it may well be difficult for them to simultaneously consider all other information related to those same firms. For example, to the extent REIT analysts and investors are focused on current period profitability, changes in FFO, pending acquisitions/divestitures, corporate governance issues, or any other firm specific attribute of the REIT, value relevant information regarding the performance of their tenants may well be overlooked, ignored, or not fully incorporated into either valuation models or investment decision making. When investors are subject to such attention constraints, the stock prices of the firms in which they invest will likely fail to fully and immediately incorporate news about related firms. As a consequence, such limited attention is likely to generate price drift. In other words, a portfolio strategy of taking a long position in REITs with good performing tenants, and a short position in those REITs with poor performing tenants, should yield positive subsequent returns. On the other hand, because the economic linkages between REITs and their tenants would appear to be uniquely transparent, ex-ante we might also expect investors to be more attentive when investing in REITs than would be the case for non-REIT real estate and/or industrial firms. As such, the exact relation between the return performance of REITs and their core tenants remains an open empirical question.

3. Data and Methodology

3.1. Data

Given the above discussion, I begin the empirical analysis by constructing a sample of firms with clearly defined economic linkages and relations. First, I identify all publicly traded equity REITs with return information available through the CRSP/Ziman database at any point over the 2000-2013 sample interval. As the focus of this investigation is on inter-firm economic linkages, those REITs specializing in mortgages, mortgage-backed securities, and residential real estate are then excluded. I next map these potential observations on to tenant rolls provided by SNL Financial, and finally determine whether each of these tenants is publicly traded with return information available through CRSP. I also note firms specializing in healthcare, industrial/office, and/or retail property investments tend to have more easily and readily identifiable tenants. For example, nearly half of all firms across these three property type sectors serve as landlords for publicly traded tenants, compared to less than one-quarter of REITs focused on investments in other property type holdings. Additional insight into the distributional characteristics of these sample firms across time is provided in Table 1. Of note, the first column reports the total number of CRSP/Ziman equity REITs specializing in any property type other than mortgages, mortgage-backed securities, or residential real estate, by year. Continuing, as the focus of the current investigation centers broadly on the return performance of economically linked firms, and more specifically on the landlord-tenant relationship, I next search the SNL Financial database to identify the core tenants for each sample REIT. I successfully identify tenants for 104 (40.6%) of my sample organizations, and report the distribution of those firms with available tenant rolls by sample year in column two.

As not all of the tenants identified by SNL are publicly traded organizations, I next determine whether each tenant is both publicly traded and has return information available in the CRSP database. Complicating this process, naming conventions are not consistent across the two data platforms, leading to a number of instances for which a single tenant exhibits multiple names. Similarly, names reported by SNL may also vary either across REITs, or over time.[3] To enhance the accuracy and consistency of my results, I use a phonetic string matching algorithm to generate a list of potential matches for each tenant name, and then hand-match tenants to the corresponding CRSP Permno by inspecting both the firm's name and industry information. To ensure tenants are matched to the appropriate stock returns and financial information, I am deliberately conservative in assigning tenant names and firm identifiers. Tenants for which I could not identify a unique match are excluded from the sample. This sorting and identification process eliminated an additional eight REITs for which I could not find adequate information regarding publicly traded tenants, leaving us with a final estimation sample of 96 unique REITs (11 Healthcare, 32 Industrial/Office, 30 Retail, and 23 Other) with non-missing CRSP tenants. Figure 1 illustrates the number of REITs in each property type category across each step of my sample construction.

Continuing, column III in Panel A of Table 1 shows the yearly number of Ziman REITs with publicly traded tenants, while Panel B reports descriptive statistics regarding the distribution of sample firm tenants found in both CRSP and SNL. In general, sample REITs lease their properties to a few dozen tenants, of which roughly half are publicly traded. I am careful not to draw definitive conclusions from these distributional patterns, as I also note the sample firms

[3] For example, the moniker J.C. Penney's and JCP are both used to identify the same retail tenant by alternative sample landlords/REITs.

exhibit considerable variation along these dimensions. Therefore, it is quite possible the economic linkages between tenants and landlords may vary markedly depending upon both the number of tenants and the geographic dispersion of the tenant base.

After identifying the 96 REITs for which I can assemble publicly traded tenant rolls, I next collect monthly returns data from the Center for Research in Security Prices (CRSP) database. To augment these return characteristics, I also collect financial statement data and additional firm operating characteristics from both the COMPUSTAT and SNL financial databases. After integrating these data sources, my final estimation sample of 96 firms includes 10,272 distinct firm-month observations, representing 1,398 unique REIT–Tenant relationships, over the interval 2000 through 2013.

Table 2 provides basic summary statistics regarding the characteristics of both sample REITs and their tenants. Panel A describes the length of the relationship between each REIT and its tenants. On average, the typical REIT in my sample is linked to its tenants for approximately 4 years. Under this initial framework, consistent with the length of the sample period, the maximum number of years a REIT is linked to its tenants is 14 years. As a number of economic relations predate the beginning of the sample period, I also provide two additional tenure metrics. First, examining only those relations which were nearly formed during the evaluation window, similar to the previously reported numbers I find my focal landlord-tenant links persist for approximately three (median) to five (average = 4.73) years. Second, extending this paradigm by assuming all economic relations which were in place at the beginning of the sample interval had been ongoing for this average 5 year cycle, I may estimate a tenure metric that is less susceptible to downward bias from sample truncation. Doing so raises the average tenure length of these "imputed" REIT-tenant economic linkages to slightly over 7 ½ years.

Continuing, Panel B provides basic descriptive information regard the operating characteristics and attributes of both the sample REITs and their primary tenants. Across this panel, all figures represent pooled firm-quarter observations, and show distributional characteristics for sample firms and their tenants including asset size, book-to-market ratios, profitability, and institutional ownership levels. Consistent with previous investigations of REIT markets during this period, the average REIT across the sample is characterized by total assets of slightly more than $3 billion. Their typical tenants are much larger in size. Not surprisingly, given regulatory distribution requirements, sample REIT book-to-market ratios hover near one. Notably, these requirements mandate REITs distribute at least 90% of their taxable income each year in order to retain their tax transparency. As such, these regulations serve to effectively limit the ability of firms within this industry to endogenously fund growth and expansion activities through retained profits, and thereby minimize deviations between firm book and market values. Consistent with this notion of regulatory constraint, tenant book-to-market ratios are significantly lower (and exhibit considerably higher variation) than those observed for their REIT landlords, reflecting (in part) the enhanced growth opportunities available to these firms. Turning to the profitability metrics, over the 2000-2013 time period, sample REITs generate on average higher accounting profits than their tenants. Given the vast array of industries within which REIT tenants operate, I make few judgements along this dimension other than to note (with some surprise) the average ROA exhibited by tenants of sample firms is actually close to zero.[4] Finally, data on institutional ownership are drawn from SEC form 13(f) filings, and reveal sample REITs exhibit average institutional ownership of 67.11%. Consistent with the previous literature (e.g., Ling and Ryngaert 1997; Su et al. 1998; and Ciochetti et al. 2002), my sample characteristics confirm both relatively high current levels of institutional ownership of REITs (67.11% for REITs vs. 61.88% for their tenants), and a strong trend toward increased institutional ownership of REITs over time.[5]

3.2. Methodology

To test my main hypothesis, I evaluate the profitability of a long–short portfolio strategy in which REITs with good performing tenants are purchased (longed), and REITs with poor performing tenants are (sold) shorted. I identify and label this portfolio as the "tenant momentum" portfolio.[6] Further, to ensure my results are not driven by either a single tenant's performance, or my inability to capture the performance of those tenants which are not publicly traded, I focus the analysis on firms with a minimum of three identifiable, publicly traded tenants.[7]

[4] I acknowledge that within REIT markets, (adjusted) funds from operations (FFO) typically serves as the primary profitability metric employed by analysts. As REIT tenants are drawn from a much broader cross section of industries, many of which do not focus on FFO measures, to facilitate comparisons across tenants and landlords our reported results employ the more traditional return on assets (ROA = Net Income divided by Total Assets) metric to assess profitability. Not surprisingly, given the relatively high degree of correlation across these metrics for sample firms, our results are robust to the use of either metric.

[5] Institutional ownership levels for REITs at the beginning of our sample interval in 2000 average only 41.62%, but grew to 70.92% by 2013. On the other hand, institutional ownership levels for sample tenants grew from 40.10% in 2000 to 68.45% by the end of our sample observation window in 2013.

[6] As the vast majority of REITs within our sample have more than one tenant, to measure the recent performance of their collective tenants I construct an equally / value weighted portfolio of their corresponding tenants and measure the performance of this aggregated tenant portfolio. Thus, within the context of the empirical results, unless otherwise noted, tenant performance refers to the aggregate performance of these conservatively defined tenant portfolios.

[7] Relaxation of this constraint leads to qualitatively similar empirical conclusions. See the Appendix for comparative results.

To construct my comparison portfolios, at the beginning of each month I rank all REITs in ascending order according to the abnormal returns of their tenants during the previous month.[8] After ranking each REIT, I next assign them to one of three tercile portfolios. All REITs are equal (value) weighted within a given portfolio. The bottom portfolio contains all the REITs with the worst performing tenants in the previous month, while the top portfolio contains all the REITs with the best performing tenants in the previous month. My focal hypothesis predicts that the alpha generated by a zero-cost portfolio that holds the top tercile of (i.e., high tenant return) REITs, and sells short the bottom tercile of (i.e., low tenant return) REITs, will be zero. In other words, in an efficient market characterized by attentive investors, this trading rule should not generate abnormal returns. Conversely, the alternative hypothesis of limited investor attention predicts a significant positive alpha for the proffered long-short strategy.[9] Thus, under the investor limited attention hypothesis, positive (negative) abnormal returns following positive (negative) tenant returns indicate the presence of tenant momentum, consistent with a slow response of REIT prices to tenant news innovations.

4. Results

Table 3 presents the cornerstone results of my empirical analysis. Across the table, I report monthly returns on portfolios of REITs formed by sorting based upon their tenants' previous monthly returns. More specifically, at the beginning of every calendar month, REITs are ranked

[8] SNL does not report the exact lease date between a REIT and each tenant. For both simplicity and tractability, I assume the link begins at the end of the year in which it is first reported. This overly conservative identification scheme reduces the power of our tests, but should enhance the validity of any relations I document.
[9] In operationalizing these metrics, I calculate abnormal returns using a time-series regression of the portfolio excess returns on traded factors in calendar time.

in ascending order on the basis of the returns to portfolios of their principal tenants at the end of the previous month. As noted above, only REITs with more than two publicly traded and identifiable tenants are included in this stage of the analysis. After ranking, each REIT is then assigned to its appropriate performance-based tercile, with tercile one (T1) encompassing REITs with the lowest performing tenants in the previous month. Terciles two (T2) and three (T3) are comprised of the middle and highest performing tenant portfolios, respectively. Across Table 3, panel A (Panel B), REITs are equally (value) weighted within each tercile portfolio.

Categorizing sample REITs according to the lagged returns of their tenants (i.e., related firms) allows us to readily observe and compare differences in the subsequent returns across tercile holdings. Examining the results in Table 3, I find that high (low) tenant returns are associated with high (low) subsequent stock returns for their related REITs. A basic/naïve "tenant momentum" strategy that is short the first tercile (i.e., low tenant return) REITs and long the third tercile (i.e., high tenant return) REITs delivers an excess return of 0.46% (t = 2.07) per month. After controlling for market risk, the aforementioned tenant momentum strategy generates results that are both economically and statistically significant, and remain very close in magnitude to the results derived under the naive model framework (0.44% per month, t = 2.01). Next, I expand the modelling approach to incorporate both the three factors proposed by Fama and French (1993), as well as the 1-year momentum factor presented in Carhart (1997).[10] Under this scenario, the ex-post performance of my sample REITs may be evaluated as follows:

[10] Consistent with the previous literature, to minimize the influence of short-term return reversals our 1-year momentum factor is measured using months t-12 through t-2.

$$\left(R_{jt} - R_{ft}\right) = \alpha_j + \beta_m MKTRF_t + \beta_s SMB_t + \beta_H HML_t + \beta_{mom} MOM_t + \varepsilon_t \quad (1.1)$$

where $(R_{jt} - R_{ft})$ is the month t excess return on the tercile j portfolio. $MKTRF$ is the excess return of the market, while the factors SMB, HML, and MOM may be thought of as zero-investment portfolios based on size, book-to-market, and 1-year momentum in returns. The results in the third row of Panel A demonstrate that my focal tenant momentum strategy, which is short the first tercile (low tenant return) REITs and long the third tercile (high tenant return) REITs, delivers abnormal returns of 0.45% per month, or approximately 5.40% per year. As such, adjusting returns to control for the REIT's own price momentum, size, and relative value does not appear to exert a material impact on the previously reported results.

Finally, in order to examine whether relative valuation differences across alternative asset classes materially influence the results, I next replicate the previous analysis incorporating a real estate factor directly into the estimation of abnormal returns. Specifically, following the expanded model framework approach of Chen et al. (2012), five-factor alphas are estimated from the following model:

$$\left(R_{jt} - R_{ft}\right) = \alpha_j + \beta_m MKTRF_{\ t} + \beta_s SMB_t + \beta_H HML_t + \beta_{mom} MOM_t + \beta_{RERF} RERF_t + \varepsilon_t \quad (1.2)$$

where $RERF$ is the excess return on a value-weighted REIT index (constructed from all publicly traded REITs). The results from this analysis are presented in the last segment of Panel A. Once again, even after controlling for the possibility of a priced Real Estate Risk Factor (RERF), I observe positive and significant returns accruing to my focal tenant momentum strategy. Interestingly, my estimated return premiums remain remarkably consistent across all model specifications, with alpha varying by no more than 4 basis points and all estimates attaining statistical significance at conventionally accepted levels.

Panel B of Table 3 presents the results of a parallel analysis in which all REITs within a given portfolio are value weighted. The results from a naïve tenant momentum strategy are reported in the first row, and show excess returns of 0.52% per month, or 6.24% per year. In the second row, after controlling for market risk, my focal result is virtually unchanged with excess market adjusted returns estimated at 0.51% per month, or 6.12% per year. Continuing, the results in row three of panel B reveal a tenant momentum strategy that is short the first tercile of (low tenant return) REITs and long the third tercile of (high tenant return) REITs delivers abnormal returns of 0.53% per month, or 6.36% per year, even after controlling for the influences of both Fama and French's (1993) three-factors and Carhart's (1997) momentum factor. Next, after controlling for the possibility of a priced Real Estate Risk Factor (RERF), abnormal returns accruing to my tenant momentum strategy equal 0.50% per month, or 6.00% per year. Once again, these estimated return premiums remain both economically and statistically consistent across alternative pricing models, varying by no more than 3 basis points and attaining statistical significance across each alternative specification.[11] Lastly, we note that estimated alphas rise monotonically across tercile portfolios, with higher alphas generated on portfolios of REITs characterized by better performing tenants. This return pattern holds across all four model

[11] Interestingly, and in direct contrast to Cohen and Frazzini's (2008) results, premiums accruing to the$2 billion tenant momentum strategy appear to be driven largely by the relatively slow diffusion of positive news rather than short side returns. While a complete analysis of this phenomenon is beyond the scope of the current investigation, one potential explanation for this differential finding flows directly from the relative transparency of REIT assets. More explicitly, Blau et al. (2009) suggest the increased transparency of REIT assets, and by extension REIT markets, reduces the ability of short sellers to predict negative future returns within this market sector.

specifications (i.e., excess returns, one-factor alpha, four-factor alpha, and five-factor alpha), and is consistently observed across both the equally weighted (Panel A) and value weighted (Panel B) portfolio returns.

5. Robustness Tests

5.1. Effect of Market Capitalization and Institutional Ownership

A number of existing papers (e.g, Lo and MacKinlay, 1990; Hou and Moskowitz, 2005) find larger firms exhibit return patterns which lead those of smaller firms, while firms characterized by higher levels of institutional ownership exhibit return patterns which tend to lead those of their counterparts with lower levels of institutional ownership. To ensure such lead-lag effects are not driving the return predictability I observe amongst REITs and their tenants, I next estimate value-weighted tenant momentum returns generated exclusively from portfolios in which sample REITs are larger (smaller) than their tenants, and from portfolios in which sample REITs exhibit higher (lower) institutional ownership than their tenants. Not surprisingly, given this estimation procedure we lose nearly half of monthly observations when analyzing subsamples where these filters are applied. The results, presented in Table 4, suggest tenant momentum return predictability is economically larger when I consider only those economic linkages where REITs are larger, or exhibit higher institutional ownership levels, than their tenants. More specifically, the alpha generated from the long-short momentum strategy implemented using the five factor model estimated exclusively on high institutional ownership (i.e., REIT I/O > tenant I/O) subsample equals 0.57% per month (t = 2.34), or 6.84% per year. Similarly, alpha generated from my tenant momentum strategy and five factor model estimated exclusively on the large firm (i.e., REIT size > tenant size) subsample equals 0.43% per month (t = 1.65), or 5.16% per year. As my focal results remain both economically and statistically meaningful within these restricted subsamples of market leading firms, I conclude lead-lag dependency effects are unlikely to account for the observed return predictability I document. For completeness, I also estimate alphas for subsamples of both smaller firms, and those characterized by relatively limited institutional ownership. Interestingly, my tenant momentum results are not observable for these subsamples. As will be expounded upon more fully in the following section, these findings are entirely consistent with predictions from the investors' limited attention hypothesis (LAH).

5.2. Variation in Inattention

If limited investor attention is driving the return predictability I document above, it stands to reason that the magnitude and significance of my results should vary systematically with both the level of investor attention, and the ease with which investors may gain insight into the firm's operations. Thus, as my next robustness test I conduct a further examination of the level of institutional ownership for both sample firms and their tenants. Institutional investors are one of the most important investor groups in the United States, and currently own or control more than half of all publicly traded equity in the United States. A broad literature exists exploring the implications of those holdings, with numerous studies documenting important economic linkages between institutional ownership levels and stock returns. For example, Nofsinger and Sias (1999) find a strong positive correlation between institutional ownership changes and firm level stock returns, while Gompers and Metrick (2001) provide evidence that the level of institutional ownership can forecast future stock returns. Similarly, Menzly and Ozbas (2010) find that the extent of the cross-predictability in returns between customers and suppliers is negatively related to the level of institutional ownership. Together, these findings suggest institutional investors possess, or gain access to, value relevant company information not widely available to alternative market participants.

Additionally, institutional investors may also play an important monitoring role within many organizations. For example, institutional investors may exert moral suasion or threaten to divest their shares in direct attempts to influence management activities and/or decision making with respect to both individual project undertakings or broad-based company strategy and initiatives. Consistent with this paradigm, a number of papers argue that large shareholders (including institutional investors) have direct financial incentives to monitor company (and management) actions, and thus play an important role in monitoring or controlling activities which may eliminate or reduce agency problems.[12] Evidence on the efficacy of such monitoring is provided by Kaplan and Minton (1994), who find evidence that the involvement of large shareholders increases management turnover; Bertrand and Mullainathan (2001), who find institutional investors monitor manager's executive compensation; Kahn and Winton (1998), who document institutional investors intervene when there is a benefit of increasing the value of their stake in the firm; and Noe (2002), who finds institutional investors can prevent managers from engaging in opportunism.

With respect to the current investigation, these findings suggest increased institutional ownership should be correlated with higher levels of investor attention through this monitoring channel. As a consequence, we would anticipate the pricing efficiency of REITs to be directly related to institutional ownership levels, while return predictability across related firms and the

[12] See, for example, Shleifer and Vishny (1986), Huddart (1993), and Maug (1998).

profitability of tenant momentum strategy should both decline with increases in institutional ownership. To explore this possibility, I estimate the following pooled regression:

$$RRET_{i,t+1} = \alpha + \beta_1 * TRET_{i,t} + \beta_2 * TRET_{i,t} * RHIO_{i,t} + \beta_3 * TRET_{i,t} * THIO_{i,t} + controls + \varepsilon_t \quad (1.3)$$

where $RRET_{i,t+1}$ is the raw return on REIT i in month t+1; $TRET_{i,t}$ is the raw return across REIT i's portfolio of tenants during month t; $RHIO_{i,t}$ is an indicator variable that assumes the value of one if REIT i's institutional ownership is higher than the sample wide REIT median institutional ownership level at time t, and zero otherwise. Similarly, $THIO_{i,t}$ is an indicator variable that assumes the value of one if REIT i's tenant portfolio exhibits institutional ownership levels greater than the sample median, and zero otherwise. Control variables include firm size (measured as the natural log of total assets) and book-to-market value ratios of both sample REITs and their tenant portfolios. Ex-ante, to the extent increased investor attention (as measured by increased levels of institutional ownership) reduces return predictability, we would expect β_2 to be negative. Similarly, to the extent tenants with higher institutional ownership attract increased investor attention, and furthermore, that such increased attention engenders positive attention spillover effects with respect to related firms (e.g., their REIT landlords), I would also expect β_3 to be negative. The results of this analysis are shown in Table 5. Examining the results, Model 1 reports the univariate relation between REIT returns and their tenants' prior performance. Consistent with my previous analysis that employed a portfolio sorting approach, these findings again document a significant positive relation ($\beta = 0.091$, $t = 18.27$) between the returns of related firms. Given the assumed lead-lag structure, these results also provide evidence of return predictability, and specifically provide further support for the profitability of a tenant momentum trading strategy. Model 2 expands my initial specification to include an interaction term between tenant returns and the indicator variable for REITs characterized by above median levels of institutional ownership. In addition, I control for both firm size and book-to-market ratios, two characteristics of REITs that could easily influence their return performance. Examining Model 2 results, the significant negative coefficient on the interaction term between past tenant returns and above average REIT institutional ownership levels is entirely consistent with predictions, and supports the notion that increased investor attention reduces both the return predictability across related firms and the profitability of my tenant momentum investment strategy. Model 3 further expands my specification to include an interaction term between previous tenant returns and tenant institutional ownership levels, as well as additional controls for both the size and book-to-market ratios of REIT tenants. In contrast to what was expected, the tenant institutional ownership interaction term does not exhibit a significantly negative coefficient. Finally, taking a slightly different econometric approach, Model 4 presents the results from the estimating equation when I cluster standard errors by firm (REIT), while Model 5 presents the results when I cluster standard errors by both firm (REIT) and year. Across each of these expanded model specifications, the results continue to support the conclusion that return predictability declines in the presence of higher institutional ownership (i.e., investor attention) levels for either the REIT or its core tenants, while interactive effects provide mixed results.

Along this same dimension, in a second robustness test I attempt to identify a subset of firms for which attention constraints are likely to be uniquely pronounced, and then examine whether return predictability is more (less) severe for those organizations. Following Cohen and Frazzini (2008), I posit that the potential for the simultaneous collection of information reduces information acquisition costs across REIT-tenant pairs exhibiting common institutional ownership.

Thus, consistent with the limited attention hypothesis, ex-ante we would anticipate firms (i.e., REITs/landlords) characterized by increased levels of common institutional ownership with their tenants should exhibit enhanced informational transparency and, as a direct consequence, reduced return predictability.

To examine this hypothesis, as outlined above, I collect data on the institutional holdings of both the sample REITs and their tenants from SEC form 13(f) filings. Operationally, I then compute common ownership (COMMON) as the number of institutions holding equity positions in both the tenant and the REIT (JOINT) divided by the total number of institutions holding equity positions in the REIT only over the same month (#TOTAL). I next divide the sample into equivalent size High and Low COMMON ownership groupings using a median split, and then reevaluate the profitability of the aforementioned tenant momentum strategy across these alternative attention based portfolios. The results of this analysis are presented in Table 6. Consistent with focal investors' limited attention hypothesis, examining these results I find strong evidence that common ownership directly impacts the information environment of sample firms. Of note, the previously documented return predictability appears to be both uniquely pronounced, and concentrated exclusively, within those organizations exhibiting relatively low COMMON institutional ownership levels. More specifically, while no evidence of return predictability is found amongst High COMMON institutional ownership grouping, the results across the low information subset are both strongly significant and evidence enhanced economic significance relative to the base case results presented in Table 3. Together, these results provide strong, supporting evidence regarding the role and importance of investor limited attention to the efficiency of asset pricing within the marketplace.

5.3. Property Type Specialization – The Case of Retail REITs

As the ease and level of information acquisition by investors may vary markedly along with the opacity of a firm's underlying assets and operations, I next explore potential differences in return predictability across property type classifications. More specifically, given the relatively high engagement factor between REIT investors and their corresponding retail tenants, I believe it is entirely possible that investors in retail REITs may pay more attention to the economic linkages between landlords and their retail tenants than would be found in other property type sectors. For example, high vacancy rates or low foot traffic at a regional mall may be readily observable by even a casual investor on an informal shopping trip, while corresponding signs of weakness for industrial, office, and/or healthcare properties may be less noticeable and only fully revealed with a lag when periodic firm disclosures are made public. Therefore, to the extent retail REIT investors are characterized by greater attention to the economic performance of related firms/tenants, we would expect retail REITs to exhibit lower return predictability than REITs specializing in other property type categories. To explore this possibility, I divide the sample into Retail versus Non-Retail REITs, and directly examine the return predictability and profitability of my tenant momentum trading strategy across these two subsamples. As illustrated in Figure 1, 31% (30 of 96) of my sample firms are classified as Retail REITs, with the remaining 69% (66 of 96) classified as Non-Retail. The results of these subsample analyses are reported in Table 7. Once again, consistent with focal investors' limited attention hypothesis, I find return predictability and the profitability of the long-short tenant momentum strategy is confined to the Non-Retail REIT subsample.

5.4 Additional Considerations

5.4.1 Alternative Portfolio Identification Strategies

To assess the validity and consistency of my core result that information travels slowly across related firms, I next entertain an alternative explanation for my findings. In implementing my original empirical tests, I implicitly assumed all landlord-tenant relations were fully and instantaneously recognized by the market. This assumption includes not only the recognition of the identities of all related parties, but also any value relevant information contained within the lease contracts formalizing those relations and/or soft information regarding future firm performance which emanates from those economic linkages. Following Cohen and Frazzini (2008), I next relax this assumption by imposing a 6-month gap between year-end dates and the stock returns I capture. This process is designed to ensure that the REIT–Tenant relations I seek to evaluate are well known and transparent to all relevant market participants long before the returns they are used to explain.[13]

Table 8 reports the results from both equally weighted and value weighted portfolios when this six month identification gap is considered. Reassuringly, the results for both equally weighted and value weighted portfolios are qualitatively identical, both economically and statistically, to the results previously reported without the six month identification gap. Of note, employing equally weighted portfolios, the alphas generated by my hypothesized long-short tenant momentum strategy under this relaxed identification scheme range from 0.36% to 0.44% per month. For comparison, recall the original values ranged from 0.42% to 0.46% per month (see Table 3, Panel

[13] This lag also mimics the standard gap imposed across the existing literature to match accounting variables to subsequent price and return data. See, for example, Fama and French (1993).

A) when I did not impose the gap. Similarly, our value weighted results under this alternative identification approach reveal returns accruing to our tenant momentum strategy range from 0.40% to 0.43% per month. These returns are again quite similar to those previously reported using value weighted portfolios, which ranged from 0.50% to 0.53% (see Table 3, Panel B). I also note the magnitude of the tenant momentum returns is once again monotonically increasing in tenant return terciles. This latter result holds across all four excess return model specifications, and is robust to the use of both equally and value weighted portfolio formation techniques. Taken together, these results strongly suggest my central findings are not driven by minor differences in the classification scheme utilized to identify related firms.

5.4.2. Longer Holding Periods

Turning to investor characteristics, from an information collection and processing perspective I anticipate that the longer an individual investor holds an investment stake within a firm, the better informed they will be regarding that organization's value drivers, and hence, the greater the information content they will be able to incorporate into prices. To test this notion, I examine the returns to the tenant momentum strategy in the three months following the portfolio formation date. Following Jegadeesh and Titman (1993), at the end of each month I rank the REITs in my sample based upon the past one-month returns of their tenants, and then group the REITs into three equally (value) weighted portfolios based upon these rankings. Each portfolio is then held for one, two, and three months following portfolio formation (note: the one month holding period simply replicates my initial, base case estimation approach found in Table 3). The alternative investment horizons I consider, along with their corresponding returns, are presented in Figure 2. Interestingly, and consistent with the investor limited attention hypothesis, I find the profitability of my focal tenant momentum strategy monotonically decreases as the investment horizon increases. Similarly, in untabulated results varying both the length of the investment horizon and the length of the portfolio formation window (also from one to three months), I again find evidence supporting my core assertions. More specifically, across all three portfolio formation intervals, I consistently observe monotonically decreasing returns to the tenant momentum strategy as the length of the investment horizon increases. The consistency of these relations across alternative portfolio strategies adds further strength and support to the relevance and importance of investor limited attention in today's financial marketplace.

6. Conclusion

This paper examines whether, and to what extent, investors' limited attention exerts a substantial influence on the return patterns of related firms. More specifically, focusing on the uniquely transparent tenant-landlord relationship across income producing properties in commercial real estate markets, I test whether the equity prices of publicly traded real estate investment trusts (REITs) fully and instantaneously incorporate all value relevant information pertaining to the financial return performance of those organizations which lease their properties. As the REIT-tenant economic linkages I examine throughout this paper are generally readily observable and represent publicly available information (particularly within the health care, industrial/office, and retail property type sectors), to the extent the market is efficient, all such information should already be incorporated into currently observable stock prices. Interestingly, however, the results of this investigation suggest investors fail to fully account for these links. A direct consequence of this limited investor attention is return predictability, which may be exploited by buying (selling) REITs following a positive (negative) performance shock to their tenants. Operationalizing this construct, I find a monthly strategy of buying REITs whose tenants generated the highest (tercile) returns in the previous month, and selling short REITs whose tenants generated the lowest (tercile) returns, yields an annualized abnormal return of approximately 5-6%. I refer to this return predictability as "tenant momentum". Through an extended series of additional tests, I demonstrate that my core findings are consistently robust across a variety of holding periods, portfolio identification strategies/approaches, alternative model specifications, and levels of investor attention (as measured by institutional ownership levels, firm size, and property type focus). In sum, the results of this investigation provide strong evidence of: 1) return predictability across related firms within REIT markets, 2) the profitability of a "tenant momentum" investment/trading strategy, and 3) the importance of investor attention to the efficient pricing of securities in general, and real estate related securities in particular.

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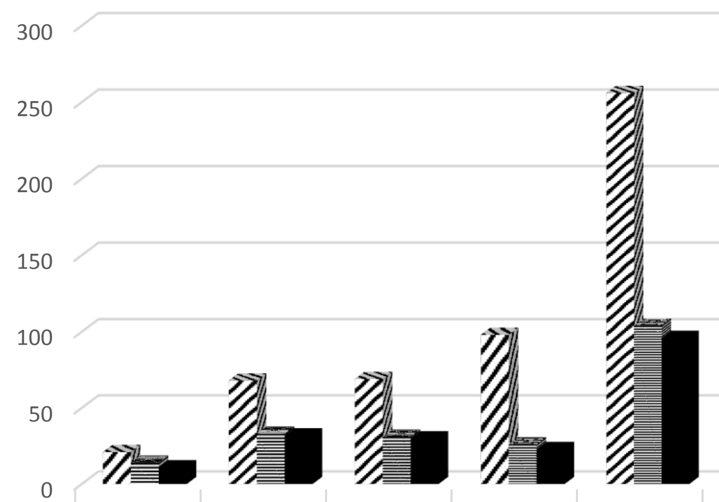
Figures and Tables



	Health Care	Industrial /Office	Retail	Other	Total
Ziman REITs	21	68	69	98	256
Ziman REITs with SNL Tenants	14	33	31	26	104
Ziman REITs with CRSP Tenants	11	32	30	23	96

Figure 1.1. Distribution of Sample Firms by Property Type Focus

This figure shows the distribution of sample REITs by the property type focus of their primary investment property holdings. The left column in each category shows the number of REITs in each category tracked by CRSP Ziman. The middle column in each category shows the number of REITs covered by SNL Financial. The right most column in each category shows the number of SNL REITs that have publicly traded tenants listed in CRSP.

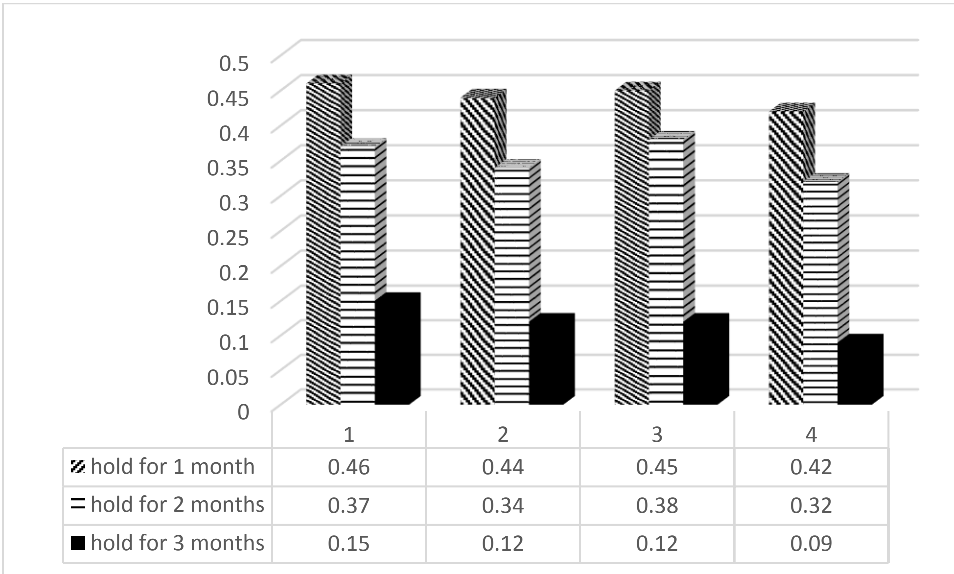


Figure 1.2. Alternative Holding Periods

This figure shows calendar-time portfolio abnormal returns for different investment horizons. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the returns to a portfolio of their principal tenants at the end of the previous month. The ranked REITs are then assigned to one of three tercile portfolios. All REITs are equally weighted within a given portfolio. Alpha is the intercept from a regression of monthly excess returns from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, the Carhart (1997) momentum factor, and a real estate factor. The real estate factor, RERF, is the return in excess of a 1-month Treasury bill of a REIT index representing the universe of REITs. The figure shows Buy-Sell alpha from a zero-cost portfolio that shorts the bottom 33% (lowest) tenant return stocks and longs the top 33% (highest) tenant return stocks. Excess returns and alphas are in monthly percentage terms. I restrict the sample to REITs with at least 3 tenants. After forming the portfolios, they are held for one, two, and three months. The left column shows the results when the holding period is one month, the middle column shows the results when the holding period is two months, and the right column shows the results when the holding period is three months.

Table 1.1. Summary Statistics of Matching Procedure

This table shows descriptive statistics regarding the construction of my sample data. Sample firm (REIT) data are drawn from the CRSP/Ziman and SNL Financial data bases. The first column shows the number of equity REITs (excluding those with an investment focus on mortgages, mortgage-backed securities, or residential property) covered by CRSP/Ziman each year from 2000-2013. Column 2 reports the number of REITs satisfying this initial condition which are included in the SNL Financial database. Column 3 shows the yearly number of REITs satisfying these initial two conditions, which also have publicly traded tenants included in CRSP. Note, I am intentionally very conservative in matching tenants reported in SNL to CRSP, and include only those firms for which I can ensure a 100% match.

Panel A. Sample Firms Over Time

Year	Number of REITs in CRSP/Ziman	Number of REITs with SNL Tenants	Number of REITs with CRSP Tenants
2000	152	32	32
2001	143	37	37
2002	138	42	42
2003	134	47	47
2004	143	52	51
2005	143	56	55
2006	129	60	58
2007	108	63	60
2008	107	64	63
2009	107	74	71
2010	116	80	78
2011	118	84	81
2012	128	87	85
2013	140	95	95

Panel B. Tenant Characteristics/Distribution

	Mean	Median	SD	Min	Max
Number of tenants in CRSP	16	14	10	1	48
Number of tenants in SNL	35	32	23	2	122
Percentage of tenants covered	41%	42%	17%	10%	100%

Table 1.2. Summary Statistics -- Characteristics of REITs and Their Tenants

This table shows descriptive statistics of the firms included in my final sample, as well as those of their core tenants. REIT data are drawn first from the CRSP/Ziman data base and then matched with coverage from the SNL Financial database. Panel A shows the time series statistics of the link duration between sample REITs and their core tenants. Panel B provides summary statistics for the pooled firm year observations from 2000 to 2013. Size is the natural logarithm of total assets. Book-to-market is the book value of equity (as reported by Compustat) divided by its lagged market value of equity. Tenant and REIT profitability is measured as net income divided by total assets. Institutional ownership data are collected from the Thomson Financial 13F Database.

	Mean	**Median**	**SD**	**1%**	**99%**
Panel B :Firms (Pooled Firm-Quarter Observations)					
REIT size ($ millions)	3,790.86	2,483.65	4,461.16	177.12	23,743.59
Tenant size ($ millions)	60,344.85	4,439.23	238,093.21	75.16	1,856,646.00
REIT book-to-market	0.84	0.73	0.64	0.03	4.22
Tenant book-to-market	0.76	0.40	1.92	-0.75	14.55
REIT Profitability: ROA=NI/TA (%)	0.57	0.59	0.91	-2.62	3.74
Tenant Profitability: ROA=NI/TA (%)	0.01	1.01	4.85	-18.84	8.29
REIT Institutional Ownership (%)	67.11	77.56	34.31	0.00	119.30
Tenant Institutional Ownership (%)	61.88	70.83	33.14	0.00	116.52

Table 1.3. Tenant Momentum Strategy, Abnormal Returns 2000–2013

This table shows calendar-time portfolio abnormal returns. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the return to a portfolio of their principal tenants at the end of the previous month. The ranked REITs are then assigned to one of three tercile portfolios. All REITs are equally weighted (Panel A) or value weighted (Panel B) within a given portfolio. Alpha is the intercept from 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 a real estate factor. The real estate factor, RERF, is the return in excess of a 1-month Treasury of a REIT index representing the universe of REITs. Buy-Sell is the alpha of a zero-cost portfolio that shorts the bottom 33% (lowest) tenant return stocks and holds the top 33% (highest) tenant return stocks. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates. I restrict my sample to the REITs with at least three publicly traded tenants with return information available through CRSP.

$$\left(R_{jt} - R_{ft}\right) = \alpha_j + \beta_m MKTRF_t + \beta_s SMB_t + \beta_H HML_t + \beta_{mom} MOM_t + \beta_{RERF} RERF_t + \varepsilon_t$$

Panel A. Equally-Weighted Returns				
	T1(Sell)	**T2**	**T3 (Buy)**	**Buy-Sell**
	1.10**	1.29**	1.56**	0.46**
Excess returns	(1.97)	(2.10)	(2.44)	(2.07)
	0.60	0.79	1.04**	0.44**
One-Factor Alpha	(1.40)	(1.61)	(2.01)	(2.01)
	0.28	0.47	0.73	0.45**
Four-Factor Alpha	(0.76)	(1.06)	(1.59)	(2.00)
	-0.14	-0.03	0.26	0.42*
Five-Factor Alpha	(-1.09)	(-0.16)	(1.06)	(1.80)
	-0.10**	-0.24***	-0.24***	-0.13*
MKT-RF	(-2.26)	(-4.00)	(-3.10)	(-1.81)
	0.16**	0.13*	0.17	0.02
SMB	(2.44)	(1.65)	(1.62)	(0.18)
	0.02	-0.05	0.06	0.04
HML	(0.45)	(-0.68)	(0.69)	(0.44)
	-0.05	-0.08*	-0.17***	-0.12
MOM	(-1.58)	(-1.78)	(-3.12)	(-2.24)
	1.14***	1.31***	1.28***	0.12**
RERF	(33.51)	(29.61)	(22.21)	(2.44)
R-Squared	*94.66%*	*92.56 %*	*88.27%*	*9.35%*
Adjusted R-Squared	*94.50%*	*92.33%*	*87.91%*	*6.53%*

Panel B. Value-Weighted Returns				
	T1(Sell)	**T2**	**T3 (Buy)**	**Buy-Sell**
Excess returns	0.87 (1.61)	1.10* (1.92)	1.40** (2.40)	0.52** (2.31)
One-Factor Alpha	0.55 (1.30)	0.76* (1.71)	1.06** (2.31)	0.51** (2.28)
Four-Factor Alpha	0.25 (0.65)	0.47 (1.12)	0.78* (1.85)	0.53** (2.31)
Five-Factor Alpha	-0.19 (-1.34)	-0.012 (-0.09)	0.31* (1.84)	0.50** (2.16)
MKT-RF	-0.07* (-1.66)	-0.18*** (-3.77)	-0.19*** (-3.55)	-0.11 (-1.54)
SMB	-0.06 (-0.99)	0.02 (0.23)	-0.01 (-0.16)	0.05 (0.50)
HML	-0.05 (-1.03)	-0.15*** (-2.69)	-0.10 (-1.51)	-0.04 (-0.46)
MOM	0.04 (1.07)	0.02 (0.69)	-0.04 (-0.89)	-0.07 (-1.31)
RERF	1.16*** (32.73)	1.26*** (35.34)	1.26*** (30.19)	0.09 (1.59)
R-Squared	*93.89%*	*94.38%*	*92.56%*	*3.45%*
Adjusted R-Squared	*93.63%*	*94.21%*	*92.30%*	*0.4%*

Table 1.4. Lead-Lag Effect

This table shows calendar-time portfolio returns. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the return to a portfolio of its principal tenants in the previous month. The ranked REITs are then assigned to one of three tercile portfolios. All REITs are value weighted within a given portfolio. This table includes all available REITs and tenants satisfying the condition on the left-hand side at portfolio formation. Size is the firm's total assets as extracted from Compustat. *IO* is institutional ownership, defined as the total number of shares owned by intuitional investors divided by the total number of shares outstanding. Institutional holdings are from Thomson Financial. Alpha is the intercept on a regression of monthly five-factor excess returns from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, the Carhart (1997) momentum factor, and a real estate factor.

	Five factor Alpha				**Excess Return**			
Restrict investment to	**T1(Sell)**	**T2**	**T3 (Buy)**	**Buy-Sell**	**T1(Sell)**	**T2**	**T3 (Buy)**	**Buy-Sell**
REIT IO > Tenant IO	-0.27* (-1.71)	0.15 (0.91)	0.30* (1.75)	0.57** (2.34)	0.78 (1.32)	1.20** (2.03)	1.30** (2.17)	0.52** (2.15)
REIT IO < Tenant IO	-0.26 (-1.27)	-0.10 (-0.51)	0.01 (0.48)	0.27 (0.71)	0.71 (1.14)	1.00 (1.30)	1.11 (1.52)	0.40 (1.00)
REIT Size > Tenant Size	0.07 (0.29)	0.14 (0.75)	0.50** (2.25)	0.43* (1.65)	1.31* (1.66)	1.40* (1.92)	1.80** (2.31)	0.49* (1.68)
REIT Size < Tenant Size	0.90 (0.44)	-0.19 (-0.66)	0.35 (1.46)	0.10 (0.78)	1.02* (1.69)	0.95 (1.27)	1.16* (1.94)	0.14 (0.44)

Table 1.5. Effect of Institutional Ownership Levels

This table shows results of a robustness test for REITs' return predictability. $RRET_{t+1}$ is the return of REITs in month t+1, $TRET_t$ is the return of tenants in the current month, and $RHIO$ is a dummy that assumes the value of one if the REIT exhibits high institutional ownership (I consider the median institutional ownership as the break point), and equals zero if the REIT exhibits low institutional ownership. $THIO$ is also an indicator that equals one if the tenant has high institutional ownership, and zero if it has low institutional ownership. Models 1, 2, and 3 control for REIT and year fixed effects. Model 4 presents the results when I cluster by REIT, while Model 5 presents the results of the regression when I cluster by both REIT and year.

$$RRET_{t+1} = \alpha + \beta_1 * TRET_t + \beta_2 * TRET_t * RHIO + \beta_2 * TRET_t * THIO + controls + \varepsilon$$

Dependent Variable is the REIT's return in the following month

	Model1	**Model2**	**Model3**	**Model4**	**Model5**
Intercept	0.013*** (29.26)	0.016*** (3.26)	0.017*** (2.99)	0.016*** (3.26)	0.016* (1.70)
TRET	0.091*** (18.27)	0.101*** (12.98)	0.104*** (11.18)	0.104*** (4.40)	0.104*** (4.33)
TRET*RHIO		-0.022* (-1.70)	-0.017* (-1.71)	-0.017 (-0.54)	-0.017 (-0.60)
TRET*THIO			-0.03 (-0.35)	-0.003 (-0.25)	-0.003 (-0.21)
RHIO		-0.003*** (-3.14)	-0.003*** (-3.45)	-0.003 (-1.35)	-0.01 (-1.18)
THIO			-0.002** (-2.05)	-0.002*** (-2.77)	-0.002*** (-2.38)
REIT Size		0.010* (1.71)	0.001* (1.80)	0.001 (0.81)	0.001 (0.56)
Tenant Size			-0.002 (-0.93)	-0.002 (-0.71)	-0.002 (-0.49)
REIT BM		-0.011*** (-10.11)	-0.022*** (-11.87)	-0.021*** (-7.01)	-0.023*** (-2.72)
Tenant BM			-0.002*** (-2.46)	-0.003*** (-4.17)	-0.003 (-1.10)
Year Fixed Effect	Y	Y	Y	N	N
REIT fixed effect	Y	Y	Y	N	N
R-Squared	0.71%	1.29%	1.34%	1.34%	1.34%

Table 1.6. Effect of Common Institutional Ownership

This table shows results from a robustness test regarding REITs' return predictability. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the return to a portfolio of its principal tenants in the previous month. The ranked REITs are assigned to one of three tercile portfolios. All REITs are equally weighted within a given portfolio. Next, REITs are further split into two groups (above and below median), based on COMMON Institutional Ownership. For each firm, "common ownership" is defined as the number of institutional investors holding an ownership stake in both the tenant and the REIT in a given calendar month (#JOINT) divided by the number of institutional investors holding an ownership stake within the REIT during that same month (#TOTAL). I report returns to an equally weighted, zero-cost portfolio that holds the top one third of high tenant return stocks and sells short the bottom one third of low tenant return stocks. Returns are in monthly percent; t-statistics are shown below the coefficient estimates.

	Five factor Alpha				**Excess Return**			
Restrict investment to	**T1(Sell)**	**T2**	**T3 (Buy)**	**Buy-Sell**	**T1(Sell)**	**T2**	**T3 (Buy)**	**Buy-Sell**
High COMMON	0.09 (0.31)	0.15 (0.66)	0.17 (0.57)	0.08 (0.31)	1.45** (2.11)	1.49** (2.29)	1.52** (2.18)	0.06 (0.24)
Low COMMON	-0.11 (-0.59)	0.08 (0.5)	0.45* (1.65)	0.55** (2.43)	1.15** (1.93)	1.43** (2.35)	1.74*** (2.64)	0.58*** (2.64)

Table 1.7. Property Type Specialization – The Case of Retail REITs

This table shows calendar-time portfolio abnormal returns. At the beginning of every calendar month, REITS are ranked in ascending order on the basis of the return to a portfolio of its principal tenants at the end of the previous month. The ranked REITS are assigned to one of three tercile portfolios. All REITs are value weighted within a given portfolio. Alpha is the intercept from a regression of monthly five-factor excess returns from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, the Carhart (1997) momentum factor, and a real estate factor. The real estate factor, RERF, is the return in excess of a 1-month Treasury bill, on a REIT index representing the universe of REITs. Buy-Sell is the alpha of a zero-cost portfolio that shorts the bottom 33% of (lowest) tenant return stocks and holds the top 33% of (highest) tenant return stocks. Returns and alphas are in monthly percent, while t-statistics are shown below the coefficient estimates. I restrict my sample to REITs with at least three publicly traded tenants with return information available through CRSP.

$$\left(R_{jt} - R_{ft}\right) = \alpha_j + \beta_m MKTRF_t + \beta_s SMB_t + \beta_H HML_t + \beta_{mom} MOM_t + \beta_{RERF} RERF_t + \varepsilon_t$$

	Five factor Alpha				**Excess Return**			
Restrict to	**T1(Sell)**	**T2**	**T3(Buy)**	**Buy-Sell**	**T1(Sell)**	**T2**	**T3(Buy)**	**Buy-Sell**
Non-Retail REITs[14]	-0.36*	-0.07	0.22	0.58**	0.66	0.93	1.21**	0.55**
	(-1.86)	(-0.48)	(1.00)	(2.41)	(1.13)	(1.62)	(2.09)	(2.21)
Retail REITs	0.33	0.02	0.37	0.00	1.35**	1.24*	1.58*	0.22
	(1.23)	(0.08)	(0.72)	(0.01)	(2.10)	(1.67)	(1.75)	(0.46)

[14] In untabulated results, I also test the return predictability for different REIT types. Industrial/office REITs generate an alpha of 0.41% per month, which is statistically insignificant. The alpha for Healthcare REITs is negative (-0.11%), and again insignificant. Finally, the alpha for Other REITs is 0.69%, and is again statistically insignificant. The detailed results of these additional tests are available directly from the authors upon request.

Table 1.8. Tenant Momentum Strategy, Abnormal Returns 2000–2013 (With Fama French 6 month gap)

This table shows calendar-time portfolio abnormal returns. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the return to a portfolio of their principal tenants at the end of the previous month. The ranked REITs are then assigned to one of three tercile portfolios. All REITs are equal weighted (Panel A) or value weighted (Panel B) within a given portfolio. Alpha is the intercept from a regression of monthly five-factor 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 a real estate factor. The real estate factor, RERF, is the return in excess of a 1-month Treasury bill on a REIT index representing the universe of REITs. Buy-Sell is the alpha of a zero-cost portfolio that shorts the bottom 33% of (lowest) tenant return stocks and holds the top 33% of (highest) tenant return stocks. Returns and alphas are reported in monthly percent, while t-statistics are shown below the coefficient estimates. I restrict the sample to REITs with at least three publicly traded tenants with return information available through CRSP.

$$\left(R_{jt} - R_{ft}\right) = \alpha_j + \beta_m MKTRF_t + \beta_s SMB_t + \beta_H HML_t + \beta_{mom} MOM_t + \beta_{RERF} RERF_t + \varepsilon_t$$

Panel A. Equal-Weighted Returns				
	T1(Sell)	**T2**	**T3(Buy)**	**Buy-Sell**
	0.97*	1.17*	1.41**	0.44*
Excess returns	(1.76)	(1.78)	(2.18)	(1.82)
	0.48	0.66	0.88*	0.40*
One-factor alpha	(1.14)	(1.22)	(1.65)	(1.67)
	0.30	0.52	0.72	0.42*
Four-Factor Alpha	(0.81)	(1.06)	(1.52)	(1.71)
	-0.10	0.01	0.25	0.36
Five-Factor Alpha	(-0.76)	(0.05)	(1.02)	(1.60)
	-0.09**	-0.32***	-0.27***	-0.17*
MKT-RF	(-2.08)	(-4.35)	(-3.26)	(-2.17)
	0.02	-0.12	0.04	0.02
HML	(0.22)	(-1.11)	(0.30)	(0.19)
	0.15**	0.17*	0.18	0.02
SMB	(2.34)	(1.67)	(1.52)	(0.22)
	-0.04	-0.17***	-0.17***	-0.14**
MOM	(-1.17)	(-3.24)	(-2.85)	(-2.26)
	1.13***	1.41***	1.30***	0.17***
RERF	(32.59)	(25.12)	(20.89)	(2.84)
R-Squared	*94.61%*	*90.26%*	*87.15%*	*10.94%*
Adjusted R-Squared	*94.44*	*89.95*	*86.74*	*8.09%*

Panel B. Value-Weighted Returns				
	T1(Sell)	**T2**	**T3(Buy)**	**Buy-Sell**
Excess returns	0.91	1.09*	1.33**	0.43**
	(1.63)	(1.75)	(2.33)	(1.97)
One-Factor Alpha	0.47	0.61	0.89**	0.42*
	(1.12)	(1.22)	(1.95)	(1.90)
Four-Factor Alpha	0.30	0.48	0.73*	0.45**
	(0.74)	(1.04)	(1.70)	(2.00)
Five-Factor Alpha	-0.13	-0.01	0.27*	0.40*
	(-0.95)	(-0.05)	(1.71)	(1.80)
MKT-RF	-0.09*	-0.15***	-0.21***	-0.13*
	(-1.87)	(-3.83)	(-3.87)	(-1.70)
SMB	-0.05	0.05	-0.01	0.04
	(-0.76)	(0.57)	(-0.12)	(0.39)
HML	-0.07	-0.16*	-0.15*	-0.08
	(-1.05)	(-1.75)	(-1.83)	(-0.70)
MOM	0.06*	-0.12	-0.02	-0.08
	(1.71)	(-2.56)	(-0.56)	(-1.5)
RERF	1.16***	1.34***	1.28***	0.12
	(32.06)	(28.45)	(30.00)	(2.06)
R-Squared	*93.83%*	*92.16%*	*92.59%*	*5.12%*
Adjusted R-Squared	*93.64%*	*91.90%*	*92.35%*	*2.08%*

Appendix

Table 1.9. Tenant Momentum Strategy, Abnormal Returns 2000–2013 (Different Number Tenants per REIT)

This table shows calendar-time portfolio abnormal returns. At the beginning of every calendar month, REITs are ranked in ascending order on the basis of the return to a portfolio of their principal tenants at the end of the previous month. The ranked REITs are then assigned to one of three tercile portfolios. All REITs are equally weighted within a given portfolio, while Alpha is the intercept from a regression of monthly five-factor excess returns from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, the Carhart (1997) momentum factor, and a real estate factor. The real estate factor, RERF, is the return in excess of a 1-month Treasury bill on a REIT index representing the universe of REITs. Returns and alphas are reported in monthly percentages, while t-statistics are shown below the coefficient estimates. In Panel A I do not restrict the sample to the specific number of tenants for each REIT. In Panel B I restrict the sample to include REITs with at least two publicly traded tenants with return information available through CRSP.

Panel A. No restrictions on number of tenants per REIT				
	T1(Sell)	**T2**	**T3(Buy)**	**Buy-Sell**
	1.13**	1.52**	1.53***	0.38*
Excess returns	(2.16)	(2.53)	(2.64)	(2.04)
	0.66	1.02**	1.03**	0.38**
One-Factor alpha	(1.63)	(2.16)	(2.30)	(2.02)
	0.34	0.74*	0.72*	0.38**
Four-Factor Alpha	(0.96)	(1.85)	(1.80)	(2.11)
	-0.06	0.29	0.27	0.33*
Five-Factor Alpha	(-0.49)	(1.59)	(1.60)	(1.80)

Panel B. Restrict the number of tenants to be greater than 2.* [15]				
	T1(Sell)	**T2**	**T3(Buy)**	**Buy-Sell**
	1.11**	1.32**	1.61***	0.50**
Excess returns	(2.05)	(2.24)	(2.62)	(2.38)
	0.62	0.84*	1.10**	0.48**
One-Factor alpha	(1.50)	(1.76)	(2.21)	(2.26)
	0.30	0.53	0.78*	0.48**
Four-Factor Alpha	(0.84)	(1.24)	(1.78)	(2.25)
	-0.11	0.05	0.31	0.42**
Five-Factor Alpha	(-0.89)	(0.29)	(1.43)	(2.02)

[15] *The results for alphas of value weighted portfolios range from 0.53% to 0.57% per month, with corresponding t-statistics ranging from 2.40 to 2.60.

ESSAY2: INFORMED SHORT SALE: EVIDENCE FROM ECONOMICALLY LINKED FIRMS

1. Introduction

Firms are economically linked to their customers and suppliers. Cohen and Frazzini (2008) document that firms' value-relevant observable information is only slowly transferred though the supply chain. They find that when a firm is listed as a major customer, any shock to a customer's stock price should also have an effect on the firm's future stock price, which means that there is a return predictability between related firms along the supply chain. The predictable large abnormal returns in supplier companies is due to the fact that the majority of investors have limited attention about the performance of customer firms and this limited attention results in informational inefficiencies and hence the return predictability. Examples of other studies that investigate investor reaction to firms' customer's performance include Pandit et al. (2011), Zhu (2014), Ahern and Harford (2014) and Hertzel et al. (2008). Of particular importance in this setting is to study whether smart investors will trade based on the economic linkage between firms and whether they help the information flow across the supply chain.

Recent studies examines the role of smart investors in information flow along the supply chain. Menzley and Ozbas (2010) find evidence that extent of return predictability in the cross sectional of suppliers and customers is negatively related to the level of information in the market that is proxied by the level of analyst coverage or by institutional ownership. Alldredge and Cicero (2014) show that insiders make profit by attentive trading based on the link between suppliers and customers. Since insiders are more attentive to their firm's customers' information, they are able to make profit based on that information. In another paper, Alldredge and Puckett (2016) investigate the significance of supply-chain relationships for institutional investors. They find that supply-chain relationships are an important determinant of institutional ownership and institutions experience abnormal trading profits in supplier firms. Guan et al. (2014) find that if sell-side analysts cover both supplier and customer they are able to improve their earnings forecast accuracy of supplier firms significantly more than analysts who only cover the supplier. These studies show that while most investors exhibit limited attention in supply chain setting, smart investors are able to benefit from the information about economically linked firms. I extend this line of literature to consider whether short sellers are informed about the economic link between suppliers and customers.

Short sellers are often viewed as informed investors who incur relatively large transaction costs to short-sell overpriced stocks and subsequently buy them back at a lower price in order to make profit. Because the potential loss associated with short selling is unlimited, they usually don't take positions in stocks unless they have information about the future return of those stocks. As such, this paper contributes to several strands of literature in finance. First, my paper adds to the literature that examines the predictive power of short sellers and whether short sellers can predict bad news (Diamond and Verrecchia 1987, Christophe et al. 2004, Christophe et al. 2010, Chakrabarty and Shkilko 2008, and Karpoff and Lou 2008). My paper, therefore, addresses the gap in the literature by examining whether short-selling in a firm in the months leading up to the firm's customer's (supplier's) negative shock is negatively correlated to the firm's customer's (supplier's) future performance. Applying Diamond and Verrecchia (1987) theory to customer and supplier news, I find that a firm's short interest contains information about the future return of the firm's customers. In other tests, I find that short sellers can predict earnings news in firm's supplier or customer. In other words, I find that the higher the level of a firm's short interest, the lower the future earnings surprise of the related firm along the supply chain (customer or supplier).

Second, I contribute to the literature on the informativeness of short sale (Dechow et al. 2001, Asquith et al. 2005 and Desai et al. 2002). While there is a large body of studies providing evidence for short seller's being informed about the future return of overpriced stocks, little is known about short sellers' informed trading in stocks of economically linked firms.[16] To fill this gap, I study short sellers' informed trading in firms' customers and suppliers. I find that suppliers with high short interest significantly underperform suppliers with low short interest, this is not the case for customers. Using only stocks in the customer firm's top short-interest quintile, a trading strategy that goes short in the supplier firms of the most-shorted quintile of stocks and long in the supplier firms of the least-shorted quintile earns a significant 38 basis points per month, or 4.56% per year. This difference is not because highly shorted stocks are predominantly micro-cap stocks, since the result is robust when I double sort stocks by size and level of short interest. Desai et al. (2002) report, for the period July 1988–December 1994, that the negative abnormal performance of stocks with high short interest persists for up to 12 months. I find this is true for suppliers but not the customers.

Finally, my paper contributes to the role of short sellers in information flow across the supply chain. Particularly, I study the relation between supplier's short selling and future return (earnings surprise) of customer and vice versa. I find that short sellers' trade help information flow

[16] Akbas et al. (2016) find that peer stocks short interest and future return is positively related.

across the supply chain. In other words, I find a negative significant correlation between suppliers' (customers') short interest and customer's (suppliers') future earnings surprise. When considering the stock return, I only find a significant negative correlation between short interest in supplier and future return of customer firms. This means that firm's short interest contains information about the future return of the firm's customers and this effect is not transient and last up to twelve months. On the other hand, there is no significant relation between a firm's short interest and its supplier's future return. However, I find that a firm's short interest is positively related to suppliers' twelve-month cumulative holding period return. Akbas et al. (2016) find that peer stocks short interest and future return is positively related, however my results cannot be related to peer companies since on average only 26% of customers and suppliers are in the same industry.

To understand better the reasons and motivation behind my study, let's look at short sellers' behavior in two suppliers of Apple, Hon Hai and Pegatron, which between them assemble more than half of Apple's iPhones and iPads. In April 2016, Apple reports negative earnings and the stock dropped more than 8 percent in the after-market session. One would expect an increase in short interest of the two suppliers after poor earnings announcement of the main customer. However, short interest in these two suppliers reached its lowest point after April 2016. This might seem counterintuitive at first, since literature provide evidence that short sellers are smart and we should expect an increase in short selling Apple's suppliers. But, on the other hand, stock prices of Hon Hai and Pegatron barely winced in April. So one might think that the link between Apple and its two suppliers are not that important but this is not the case. In fact, short sellers started to trade the two suppliers' stock months before Apple release its earnings announcement. Figure 1 shows the increase in short interest in Hon Hai and Pegatron st several months before Apple's earning announcement in April.

I argue that the information content of short interest for related firms' stocks along the supply chain would be short sale constraints. The negative relationship between firm short interest and future returns (earnings surprise) of the customer firm is driven mainly by stocks with the highest customer's short interest. Thus a firm's short interest predicts future stocks performance of the firm's customers mostly when the level of short interest in the customer firm is high. Fully exploiting firm-specific private information may be costly when shorting constraints bind. These informed traders, to reduce their trading costs, may then have incentives to strategically make information-based trades in the stocks of supplier firms. I find results consistent with this explanation. Using regression analysis, I also find that customer firm's short sellers are informed about the future earnings of supplier firm. In other words, I find a negative relation between customer short interest and next quarter supplier earning surprise.

The remainder of this paper is organized as follows. Section 2 provides a thorough review of previous studies, Section 3 describes the data. Section 4 presents the main empirical results and outlines some implications of results, while Section 5 concludes.

2. Literature Review

In this section, I go over the related literature in more detail. Since my paper contributes to investor attention, economic links between firms, and the role of smart investors in related firms, I will elaborate the literature and motivation in this section.

2.1. Investor Attention

This paper contributes to the literature of investors' limited attention and hence their underreaction to firm specific news. Due to cognitive capacity constraints, investors may not be able to consider all the information at the same time. As a result, they may focus on one particular set of information about a firm. For example, if an individual focuses on understanding the implications of the financial report of one firm, he may be unable to study more complex information carefully at the same time. Some literature finds evidence of investors' underreaction to firm specific information such as the information of the other firms that are related to it.

Dellavigna and Pollet (2009) study investor's limited attention on Friday earnings announcements and whether it affects the stock prices. The objective of the paper is to provide evidence that investors have less attention on Friday comparing to other weekdays. Therefore, there will be more drift for Friday announcements and fewer trading volume. As a result of investors limited attention we expect lower immediate response and higher delayed response on Friday earnings announcement. They find that more than 80% of announcements occur on Tuesday, Wednesday, or Thursday, 13.8% occur on Monday, and only 5.7% are on Friday. Another finding is that Firms announcing on Friday have more negative earnings surprises and 10% smaller market capitalization. Then the paper tests the stock price responsiveness to Friday earnings versus to non-Friday earnings. Compared to non-Friday announcements, Friday announcements exhibit more delayed response and the delayed response is more pronounced for negative surprises. The top-to-bottom return for a Friday announcement is (marginally) significantly smaller than that of non-Friday announcement (-0.88%) for immediate response. For delayed response, the estimated post-earnings announcement drift for Friday announcement compared to non-Friday is positive and significant. The results are consistent with the predictions of the model if more investors are inattentive to the information released on Friday. For Friday announcements, inattention leads to less immediate response, and more delayed response, as investors become aware of the neglected information.

Hirshleifer et al. (2009) study investor inattention and how it can results in market underreaction. Investor inattention occurs because it is hard to deal with multiple information sources or perform multiple tasks at the same time. In their paper, the authors test the investors' attention when there are other earnings announcements on the same day that the firms announce its earnings. To test the distraction hypothesis, first stocks are quarterly sorted based on each firm's earnings surprise and then by the number of earnings announcements by other firms on the same day as the firm's earning announcement. Then according to the number of announcement in each day ten decile are constructed. The top decile is the "high news day" and the bottom decile is the "low news day". In each announcement decile, the mean announcement period CAR[0,1] and post-announcement period cumulative abnormal returns CAR[2,61] are calculated for the most positive and the most negative earnings surprise deciles. A larger spread for CAR[0,1] indicates that investors react more strongly to earnings news on the announcement date. A larger spread for CAR[2,61] means that investors show more underreaction to earnings news and there is more PEAD. The intuition is that on high-news day the degree of investor's inattention increases which leads to more market underreaction and hence stronger PEAD for the firm. The distraction hypothesis in their paper is that CAR[0, 1] spread should be smaller and CAR[2,61] should be larger for high news day. The results show that the price reactions to earnings news and post earnings announcement drift are stronger when earnings are announced on high news day. The main finding is that Investor's announcement day reaction to earnings news is significantly less sensitive to earnings news on high-news days than on low-news days. In other words, when there are more competing announcements on the same day, then the investors are less attendant to the earnings news. It is found that the abnormal trading volume is significantly lower when the earnings announcement occurs on a high-news day comparing to when it occurs on a low-news day. The paper also compares the distraction effects of industry-unrelated versus industry-related announcements, big versus small earnings surprises, and large versus small firm announcements. The findings are that for industry unrelated announcement and big earnings surprises and has a stronger distraction effect. However, surprisingly the announcement of larger firms has a weaker effect on the distraction effect.

Hirshleifer et al. (2011) provide a theoretical model for stock return misreaction to earnings announcement when there is investor's limited attention. They show that different earning's components explain both underreaction and overreaction to earnings announcements. The model offers empirical implications about the determinants of the strength of the misreaction effects. Previous literature shows that there are both underreaction and overreaction to earnings information of a firm. Hirshleifer et al. (2011) considers earnings components. In other words the information contained in earnings is divided into information in cash flow and information in accruals. In the model, an investor who attends to earnings but does not impound the information in earnings components into his valuation overvalues high-accruals firms and undervalues low-accruals firms. In the model there are two components of earnings (earnings=cash flow + accruals) and three types of investors; One set of investors are completely inattentive, the second group are those who attend only a subset of the earnings related information and the third group are those investors who attend all publically available information. An attention proxy used in their study is the share ownership of institutional versus individual investors. If institutional investors are attentive to accruals, cash flows, and earnings, then high institutional ownership and low individual ownership should be associated with more earnings and accrual anomaly. Implications for empirical work are as follows: (1) if there are some investors who neglect the information in current-period earnings as well as cash flow and accruals, then more positive earnings surprises are associated with greater undervaluation of the firm, and more negative surprises with greater overvaluation; and there is post earnings announcement drift. (2) The average price reaction to the earnings surprise and average PEAD increase with the earnings surprise (3) The higher the percentage of neglecting investors to earnings, the weaker the average immediate reaction to a given earnings surprise, the stronger the relation of misvaluation to the earnings surprise, and the stronger the PEAD. (3) A firm with date 1 high (low) cash flows is undervalued (overvalued), and subsequently on average earns positive (negative) abnormal returns. (4) If the fraction of investors who are unattended to earnings, accrual and cash flow is sufficiently small relative to the fraction of investors attendant to earnings but unattendant to the components, a firm with date 1 accruals that are above (below) their unconditional mean is overvalued (undervalued) and subsequently on average earns negative (positive) abnormal returns.

Brown (2014) studies information processing constraint effect on asset mispricing. The event studied is Tennis Championships. There are several reasons to choose this event for this study; first, there is a clearer separation between zero-information periods and information periods than could be expected in any financial market. In other words before the match there is no information. Secondly, it takes hours for the information to reveal and it allows the author to take a look at price changes in the presence of information. Another advantage if this event is that it allows the author to differentiate between the ability to process the information and the ability to receive the information. If traders update the value of one of the assets that they are trading after viewing the progress of the match this implies that they have received the necessary information to update the value of the other assets that they are trading. Therefore, if mispricing between the two assets is due to cognitive limitations, it should be a result of constraints on my ability to process information, rather than constraints on my ability to receive information.

The paper defines two markets; win market and set market. The win market is where bets are traded on the winner. The set market on the other hand, allows for betting on the specific score by which each player wins. Mispricing is then defined as the absolute difference between the implied win probability in the win market and the implied win probability in the set market. A set of regressions are done. The dependent variable is mispricing and the explanatory variable of interest is a dummy equal to one if the period is during the match and zero otherwise. The paper finds that the arrival of information into the Tennis competition means that the traders' information processing constraints become binding and it is a cause of asset mispricing. The magnitude of mispricing is higher during the arrival of information period comparing to the period of zero information.

Peng et al. (2006) is a theoretical paper about investor attention. It studies the effect of investors' inattention in asset pricing. It shows that investors with limited attention tend to focus more on market- and sector-level information than on firm-specific information. They show that there is asset return predictability in presence of investors' inattention and it increases with investor's overconfidence.

Huang and Liu (2007) is another a theoretical paper. The authors show that investors' inattention to important economic news is rational when information production and information processing is costly. They developed a model and show that rational inattention changes the optimal trading strategy and as a result investors might underinvest or over invest. They also show that higher risk averse investors or investors with higher investment horizon chooses less frequent but more accurate periodic news.

Loh (2010) studies Investors' under-reaction to stock recommendations. There is a predictable drift after analysts' recommendation because the information did not get fully incorporated in the stock price when the recommendation was released. For the downgrades it might be possible that the underreaction is because of short sale constraints but there is no clear reason for upgrades. Loh states that investor inattention can explain the post recommendation drift that is due to investor's under-reaction. He uses by using prior turnover as a proxy[17] for attention. The main finding is that low-attention stocks react less to stock recommendations than high-attention stocks around the three-day event window. Subsequently, the recommendation drift of firms with low attention is more than double in magnitude when compared to firms with high attention. Each day, firms with recommendation changes are sorted into high prior turnover and low prior turnover groups. Then the response of investors to rating changes issued for these two groups are compared. The hypothesis here is that for low attention firms, the recommendation changes have weaker reactions which means that low attention firms have stronger drift. Basically the author examines the following hypothesis: Hypothesis 1a: The magnitude of stock

[17] Hou et al. (2006), using share turnover as a proxy for investor attention, demonstrate that an earnings momentum strategy is more profitable when investors are inattentive.

recommendation reaction for firms with low prior turnover is smaller than that for firms with high prior turnover. Hypothesis 1b: The magnitude of stock recommendation drift for firms with low prior turnover is larger than that for firms with high prior turnover. Hypothesis 1c: The proportion of return on the recommendation date as a percentage of the total recommendation return is smaller for low prior turnover firms. Analysist recommendation data are from Thomson financials I/B/E/S US from 1993 to 2006. The results are robust to controlling for other variables that could be associated with trading volume such as illiquidity and uncertainty. The results also hold for alternative proxies for attention.

Ramnath (2004) examines the investors' reaction to the performance of the firms' peers in the same industry and find investors' underreaction. While most of the literature finds that there is investors' underreacting to the related firm's news, some papers find the opposite results; Thomas and Zhang (2008) study that how the stock price of a late announcing firm can be affected by early announcements of its peer firms. In other words, they investigate the information transition between a firm and its peers when they announce their earnings earlier. The authors state that if the information of the early announcing peer firms is incorporated in the stock price of the late announcing firm then the price of late announcing firm cannot be predictable. The results of their paper show that there is a strong negative correlation between the two prices meaning that there is an overreaction to the early announcement of firms in the same industry. And the overreaction is corrected when the earning announcement of the late announcing firm is revealed. My paper however, contributes to the vast literature on investors' limited attention and their underreaction to information in financial markets.

2.2. Related Firms

According to Cohen and Frazzini (2008) when a firm is listed as a major customer in a supplier firm, any shock to a customer's stock price should also have an effect on the supplier's stock price. They find that a large drop in the customer firm stock price leads to a gradual decrease of the supplier's stock price in the following months. Furthermore the predictability of the supplier's return is possible for a period of 6 to twelve months. This is because the information about the customer's stock is not directly incorporated into the suppliers stock price, which suggests that investors are inattentive to the news of linked firm; The information available is not processed directly by the investors as they are mostly specialized in their own segments of the market. However, if the investors are smart and consider the economic link between two firms, then supplier's stock price will adjust and the magnitude of the return predictability will decline when the news about the negative shock to the customers firm is published.

Ahern and Harford (2014) use data from BEA (Bureau of Economic Analysis). This data set contains all Input and Output trade flows between all producers and buyers in the United States. Producers include all industrial, service and household sectors. Buyers include industrial, households, and government sectors. Therefore this data set does not include industries. The number of reported industries in BEA is from 411 to 478. Ahern and Harford (2014) first models a network of all industries in the US. Each industry is connected to the other industry through customer-supplier trade flow. The implication is that any economic shock should transfer along this network and the shock travel should be predictable. The economic shock studied in the paper is merger waves. There are three hypotheses considered by Ahern and Harford (2014): first, mergers in different two industries occur when the two industries have strong trade flows. Second, mergers wave spread across industries with have customer supplier link. Third, the structure of customer-supplier network determines which industries are involved in the wave. The first finding is that mergers happen rarely in industry pairs. In other words, only 6% of industry pairs experience mergers. The authors find that the pattern of cross-industry mergers is very similar to the cross-industry trade flows. They find that almost only 5% of industry pairs have trade flows. For example, industries that have the strongest trade flow in the customer-supplier network (central industries; it has the most connections to other industries) and industries that have the most trade flows (clustered industries; how embedded a node is in the network) also have these characteristics in the merger network meaning that they are more central and clustered in interindustry mergers. The second finding is that in customer –supplier network the closer the industries are to each other in terms of trade flows the more they have merger activity in the following year but if the two industries are not close then the merger activity occurs after two or three years. Therefore the merging activity would be like a wave in the customer-supplier network.

In another study, Menzly and Ozbas (2010) investigate the cross return predictability of industries and stock along the supply chain. They show that the extent of cross-predictability is negatively related to the level of analyst coverage or by the level of institutional ownership. They also find that institutions increase (decrease) their ownership in a stock at the same time that they increase (decrease) their ownership in supplier and customer industries. The last finding is that a trading strategy of buying industries with high returns in supplier (customer) industries over the previous month and simultaneously selling industries with low returns in supplier (customer) industries over the previous month yields an annual premium of 7.3% (7%). In their paper they also use The Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA) to identify supplier and customer industries for two reasons. First, only the smallest stocks exhibit cross-predictability effects based on lagged COMPUSTAT customer returns. This raises questions as to whether return cross-predictability is an economically important phenomenon worthy of study if it is limited to small stocks. Second, using the customer information database to identify supplier firms (in effect, by using reported relationships in the reverse direction) and then testing for cross-predictability effects from supplier firm yield no significant results. This is because the customer firms reported in COMPUSTAT are typically much larger than the reporting firm. In comparison, the BEA Surveys enable us to identify, for each firm, broad portfolios of supplier and customer firms whose returns contain economically important information regardless of the size of the firm in question. As a result, cross-predictability effects based on the BEA Surveys are robust even to the exclusion of small stocks. The main hypothesis in the paper is that firms along the supply chain have correlated fundamentals. The other hypothesis is that stock-level returns are cross-predictable. The results are consistent with the hypothesis that the return of the stock is predictable from the lagged return of its supplier and customer. The paper also shows that the degree of cross-predictability is lower where there are more informed investors (analysts and institutional investors).

Pandit et al. (2011) studies the economic determinants of information externalities by the supplier. The authors study the factors that affect the effect of customer's return around its quarterly earnings announcements on the supplier's return around that time. The contribution of the paper is that the information externality is not limited to firms in the same industries but it also exists along the supply chain. In this study the direction of information flow is from customer to supplier. They first find evidence that there is actually an information externality experienced by the supplier at the time of customer’s QEA. The information externality experienced by the supplier is increasing in: (1) the magnitude of the news contained in customers’ QEAs (2) the strength of the economic link between a supplier and its customer; (3) customers’ COGS; and (4) the level of uncertainty at the time of customer’s QEA and it is decreasing in supplier’s earnings persistence.

Zhu (2014), by using 1083 unique link of firms and their customers from 1983 to 2011, shows that the supplier’s return is predictable from the firm’s earnings announcement. In other words, Zhu studies whether market underreact to customer earnings announcement as a result of investors’ inattention. The author provides evidence that the supplier‘s three-day cumulative abnormal return is positively affected by the customer earnings announcement around the announcement day. So there is immediate responsiveness of supplier’s stock returns surrounding customer announcements. This result is in contrast with Cohen and Frazzini (2008) who report that stock prices do not fully reflect news involving related firms, which generates predictable subsequent price moves. The author also looked at the responsiveness of the supplier stock price to the customer earnings announcement following the announcement. He finds that when customer earnings surprise changes from lowest decile to the highest decile then the delayed abnormal return of the supplier would increase. This results support the hypothesis that the investors’ inattention causes market underreaction. The paper also studies how much the post earnings announcement drift in customer returns results in supplier’s delay in adjusting the price. Because the PEAD of customer results in customer higher post return and this translates to supplier’s higher post return. So the predictability of the supplier’s return is due to higher customer’s return therefore in this case there would be no investor inattention and investors are rational and take into account the link between supplier and customer however the PEAD of customer leads to the delay in suppliers return. He finds consistent results.

Banerjee et al. (2008) argue how supplier-customer link affects the capital structure decisions of firms in the Compustat database. First, their paper shows that the debt ratio of firms in durable goods industries is decreasing in the importance of purchases from suppliers who are dependent on these firms for a major part of their sales. In bilateral relationships, particularly in durable goods industries, it is likely that the produced product is unique, therefore it requires specific investment. On the other hand, if a firm has several customers then the product is more likely standardized instead of being unique. The main hypothesis is that the customer's leverage (debt ratio) is lower when the input from its dependent supplier is more important. And the effect is stronger when the customer is in an industry with durable product. The supplier-customer link can also affect the leverage of the supplier. Because suppliers are less diversified their survival depends on the business with their customer and the loss of business might destabilize them. Therefore the supplier might have lower leverage. The second hypothesis therefore is about the supplier firm; a supplier has lower debt ratio if he link with its customer is more important practically in the case of durable goods industries with unique product. The data are from Business information Compustat segment file. The sample is from 1979 to 1997.Regression analysis is done for empirical study. The dependent variable is therefore the market leverage of the firm, where the market leverage, is defined as the ratio of long-term debt to the market value of equity plus total debt. The independent variables are purchases from dependent manufacturing suppliers from different sectors as a fraction of Cost of Goods Sold of the customer firms. The sample is divided according to whether the firms belong to the durable or nondurable goods manufacturing sector.

The results show that durable sector customers who rely on dependent suppliers for a larger proportion of their inputs maintain significantly lower market leverage. But in nondurable goods manufacturing sector, the effect is not significant. The intuition is that when specific investments are more important, customers choose lower debt ratios to encourage more specific investment by dependent suppliers in the durable sector when they purchase more from them. The same regression analysis for suppliers show that suppliers in durable manufacturing sectors have lower debt ratios to reduce the costs of financial distress that would have to be incurred in the event they lose their principal customers.

Cheng and Eshleman (2014) show that the supplier shareholders overreact to customer earnings news because that news contains imprecise information about the supplier's future cash flows and this overreaction will be corrected when the suppliers announce their own earnings. The evidence shows that supplier's abnormal returns around its earnings announcement are negatively correlated with supplier abnormal returns at the earlier customers' earnings announcements. The negative correlation means that the supplier's shareholders are overreacting to the customer's earnings announcement. The degree of overreaction, however, depends on how strong the link is between supplier and customer. If they are strongly economically linked, then the degree of overreaction declines. The information regarding the firm's main customers gives an imprecise signal about the firm's future cash flow, since good or bad news for a customer does not always translate to good or bad news for the supplier. For instance, there might be some segments of the customer firm with increased sales but these segments are unrelated to the supplier. Therefore, in this case customer's earnings announcement might have good news which does not give a signal about the supplier's performance. The sample includes 45,319 supplier-customer-quarter observations. Data are from 1976 to 2009 from Compustat Segment file. The data that supplier's earnings announcement is before the customer's earnings announcement is removed from the sample. Cheng and Eshleman (2014) use both portfolio approach and regression analysis. Their paper focuses on the quarterly earnings announcements of a firm's customers, rather than its suppliers.

In another paper, Fee et al. (2006) study about the relation between supplier and customer. The paper studies whether the customers have an equity stake in their suppliers and what factors are important in having ownership in the supplier firm. The authors used a sample of more than 10,000 separate links between customer and supplier from Compustat segment file. The data are from 1988 to 2001. The main findings of the paper is that the factors that are most important in having equity stakes in the supplier firm is the percentage sales of supplier to customer or in other words the degree of supplier's dependence on the customer. Secondly, they find that in general most customers don't have shares in their supplier (only 3% of the sample). Another finding is that equity stakes are more common when the supplier is a R&D intensive firm which means that the annual expenditure on R&D is high relative to the total asset. Next, the suppliers with negative free cash flow are more likely to have their customers as block holders. If the customer has ownership in its supplier, then the link between the two lasts longer, because in this case, customer will also represent on the supplier's board. Age and size of the suppliers are studied relative to the customers. Suppliers are much smaller but younger and younger suppliers are more likely to have an equity hold by the customer.

Another example of studies about information transmission between supplier and customer is the study done by Hertzel et al (2008). They study whether a firm's industry rivals, suppliers or customers responses to its financial distress. The analysis of customers and suppliers in the paper provides a better understanding of how impairment (both economic and financial) at one firm can ripple through other layers of the supply chain. In addition to the effects of bankruptcy filings, the effects of pre-filing distress on rivals, suppliers, and customers. The data of bankruptcy filings are sample of 1,695 bankruptcy filings between 1978 and 2004 from Bankruptcy DataSource Index. The firm's customers are extracted from Compustat Segment file, since public firms disclose the amount of revenue derived from each customer that accounts for at least 10% of total revenue. To form the firm's suppliers, all Compustat firms that list a filing firm as a ''major'' customer are identified by employing a text-matching program to match the text abbreviation for the customer's name to one of the filing firms and then they are visually ensured for accuracy. The matches are restricted to five years prior to filing date. To form the sample of customers, the process is reversed and all Compustat firms listed by the filing firms as major customers are identified. There is an asymmetry in the customer and supplier sample, because while the procedure identifies customers that are important to the filing firms, it is not necessarily that these customers are reliant on the firms (suppliers are more reliant than customers on the filing firms).Therefore, the paper also examines a subset of reliant customers defined as those for which purchases from the filing firm scaled by total cost of goods sold is greater than 1%. For the full sample of 250 filing firms, they identify a total of 311 customers and 275 suppliers. Furthermore, neither suppliers nor customers appear to be significantly impaired by the filing firm's bankruptcy, i.e. their abnormal returns are insignificantly different from zero when horizontal rivals experience positive returns in the filing period.

Harford et al. (2017) study the effect of economic link between firms on the merger activity. In other words, they investigate how the economic linkage affect the probability that the firm become acquired, which firms are most likely merged, which target attracts more bidders, and which mergers have the greatest effect on the merging value. The paper explains that acquisition not only affects the firms involved in it but also it has an -impact on the firms that are economically linked to the target or acquirer. Economic link between firms increase the probability that one firm acquire the other one. Two firms might be connected through social network among boards or through supplier-customer link, however, the paper only considers the supply chain type of connection because it mostly leads to social connection. Making an acquisition across a customer-supplier link is one way to protect relationship-specific investments, and better expand the investment. The first hypothesis is that bidders are more attracted to firms with many economic links, for instance a firm with many customers. The second hypothesis is that the more a firm is economically linked to other firms the stronger the merger value creation is. The data are from Compustat Segment File from 1991-2009. There are some unobserved connections in this data set because it only includes the customers that account for 10% or more of firms' sales. Therefore any connection with less than 10% sale is ignored. The paper uses BEA data set in order to include the average industry input outputs to control for these unobserved connections. The 10% cutoff in the dataset might have size concern, in other words, the customer supplier connection is only proxing for size. It might include only small firms because the only firms with huge customers are small firms. But, the authors show that the average size for acquirers/targets with large customer is very close to average size of acquires/targets without large customers. The mergers and acquisition data are extracted from SDC. The paper uses logit regression to investigate the effect of customer-supplier link on merging probability. First, they define different measures for economic ties of the acquirer or target. These measures are direct or indirect. The measure of direct vertical connections identify when target or acquirer is a customer of the other one. An indirect connection is when both firms supply to the same customer, both firms are customers of the same supplier, or both firms are in the same industry. Direct measure is like the firm's centrality (number of customer or suppliers it has). The dependent variable is an indicator variable that takes one if the firm is a target or acquirer and zero otherwise. Other control variables include the firm characteristics for acquirer and target. The matched sample of 5 pseudo-deals per real deal was obtained by matching the 5 nearest neighbors by propensity score using non-network control variables. The results show that it is more likely that firms acquire their customer than acquiring its matched peers or be acquired by their supplier than being acquired by matched peers. In addition merging is more likely when the two parties share a common customer or supplier. Rival firms or firm within the same industry are also more likely to merge compare to matched peer firms. For the second hypothesis that how much the economic link between the two parties affects the merging value, mutivariate regression is done with acquirer's announcement return (CAR(-1,+1)) as dependent variable and measure of direct and indirect economic ties as explanatory variables. Direct measure of economic link are considered when two firms are linked together through customer-supplier link or in other words one of them is customer and the other the supplier, and indirect measure is when two firms share a common supplier or customer. Evidence is consistent with the hypothesis that mergers with more economic links create more value.

2.3. The Role of Informed Traders in the Stock Market and Related Firms

My study investigates the role of short sellers in related firms. There is a large body of literature which suggests that short sellers are informed about future returns. Boehmer, Jones and Zhang (2008) find that short constraints are not widespread since shorting account for more than 12.9% of NYSE volume. They state that short sellers are informed and contribute to efficient stock prices, particularly institutional short sales are the most informative. The sample they use consists of all NYSE system order daily data records related to short sales from January 2000 to April 2004. To find the cross section of short selling and future return of stock, the authors first do the single sort. According to the authors the portfolio approach is the best way to measure the cross sectional differences. Because first it minimizes the effect of outliers and second because it is easier to interpret. For single sort, on each trading day firms are sorted into based on the short-selling activity measure (number of shares shorted and shorting's share of volume[18]) over 5 trading days and then quintile portfolios are constructed. Then value-weighted portfolios are held for 20 trading days. Then Daily calendar-time returns and Fama and French (1993) three-factor alphas are reported. If short sellers are informed, then we expect that the excess return and Fama French three factor alpha be negative for heavily shorted stocks portfolio (bottom quintile) and positive for lightly shorted stocks (top quintile) portfolio. The results show that Fama French alpha for heavily shorted portfolio is on average –0.24% per month and for lightly shorted portfolio is 2.55% per month. These numbers show that short sellers are relatively informed about the stock and avoid

[18] They find that the standardized shorting measure (shorting's share of volume) has a more modest but opposite correlation to market cap. On average, large stocks tend to experience light shorting by these measures. But unstandardized short measure which is the number of shares shorted is positively related to the size of the stock. Which make sense since larger cap stocks have more shares outstanding.

the undervalued stocks. However, the alpha for heavily shorted stock portfolio is -0.24 or almost zero so we cannot say that short sellers are mostly interested in the overvalued stock. Boehmer et al state that short sellers keep prices in line rather than bringing prices back into line. They also look at the return spread between the heavily and lightly shorted portfolios and found that heavily shorted stocks underperform lightly shorted stocks. The authors also look at the double sorting results to confirm that the results are not simply because of characteristics that are associated with cross-sectional differences in average returns. The methodology is that first stocks are sorted into quintiles based on size, market-to-book, stock return volatility, or turnover for the previous month and then within a characteristic quintile, they are sorted based on shorting flow over the past 5 trading days. The results are still consistent with the hypothesis after controlling for characteristics that affect the stock return. Another findings of the paper is that compared to stocks that are lightly shorted by institutions, the quintile of stocks most heavily shorted by institutions in a given week underperforms by 1.43% over the next 20 trading days (more than 19.6% on an annualized basis).

Diether et al. (2009) find that short sellers 'trades correspond to 31% and 24% of share volume on Nasdaq and the NYSE, respectively. This means that the costs of borrowing stocks for short sales are not constraining US short sellers significantly. They also find the determinants of short shelling activity. The paper finds evidence that short-selling activity is higher for large-capitalization stocks, growth stocks, stocks with high institutional ownership, high price stocks, and stocks with actively traded put options. The paper finds evidence that short sellers increase their activity after periods of positive returns, on days with significant buying pressure, and on days with high levels of asymmetric information. It shows that short-selling activity is associated with negative abnormal future returns. A strategy that goes long in stocks with low short-selling activity and sells short stocks with high short-selling activity would generate significant positive abnormal returns of roughly 1.4% per month. Using regression approach, the paper finds that both high short-selling activity and high buying pressure today predict significant negative future abnormal returns. Another finding is that higher short-selling activity today is associated with subsequent decline in buying pressure. Overall the evidence in the paper supports the hypothesis that short sellers help correct short-term stock price overreaction to information. To show that short sellers trade on short-term overreaction and increase their shortselling activity after periods of high returns, the paper uses panel data; short sales during day t are regressed on past 5 days return including control variables. The control variables are current return, the day t stock-level effective spread, daily buy-order imbalance , the difference in the high and low price on day t divided by the high price: (high − low)/high, average daily σ from day t − 5 to day t – 1, average daily share turnover of a stock for day t − 5 to day −1, a dummy that equals 1 if a stock is in the lowest (highest) r−5,−1 quintile for NYSE (Nasdaq) stocks. Coefficient of past return in the regression is highly significant (positive coefficient) in univariate setting and also highly significant even after including the controls. In order to show that increased short-selling activity should predict future abnormal negative returns, the paper applies portfolio approach; the authors first compute short activity quintiles for each market on date t and form portfolios on day t using stocks with a closing price on day t − 1 greater than or equal to $5. They then compute size and book-to-market adjusted returns based on the standard 25 value weighted portfolios (Fama and French, 1993) for each portfolio. The portfolios are value weighted and rebalanced daily and skip one day (t+1). The holding period is once considered only t+2 and once t+2 to t+5. If short sellers can predict the future return then the portfolio that includes stocks which are heavily shorted on day t has negative abnormal return and the difference in high and low portfolio (low-high) has positive abnormal return. The results are consistent with the hypothesis.

Hirshleifer et. al (2011) test whether short arbitrageurs respond to firm overvaluation, and whether they succeed in correcting it. The overvalued firms in this study are those firms which have had high accruals at the end of the previous year. According to Fama and French (2010) accrual anomaly is among the most pervasive financial anomalies. Under this hypothesis, high accrual firms are overvalued, and have subsequent low abnormal returns when this overvaluation is corrected. Similarly, low accruals cause undervaluations. And firms with low accruals have subsequent positive abnormal returns. Therefore, accrual anomaly causes market inefficiency.

Since short sellers are informed, it is expected that they would increase their activity in firms with high accrual anomaly. Therefore the test done here is first a univariate test. In this test, the authors examine whether the relation between short interest and accruals is positive. They find strong evidence of this hypothesis. Particularly, they find that high-accrual firms have higher short interest. In this test they construct decile portfolios based on accruals. They find that short arbitrage activity is mainly limited to the top accruals decile. In addition they tested whether the effect is different between NASDAQ and NYSE. They find that short arbitrage of accrual anomaly is stronger among NASDAQ firms, for which the mean short interest in the highest accrual decile is over 40% higher than the mean short interest of the lowest accrual decile. Hirshleifer et. al (2011) also test whether short arbitrage constraints cause asymmetry in return predictability on the short side of the accrual anomaly relative to its long side. The asymmetry in return predictability in the paper is defined as the difference of absolute returns in top-decile and bottom-decile and it is used as an indicator of the relative effectiveness of short versus long arbitrage. They also examine a multivariate test that includes controls. They find a significant positive relationship between accruals and short interest even in multivariate test. In his paper they consider institutional ownership as a proxy for easiness of short arbitrage. Because more institutional ownership means that there are more loanable shares available to borrow. They added an interaction term of IO*accrual in the regression. They find that for the firm which the Institutional ownership is higher, the effect of short arbitrage of accrual anomaly is stronger. They also control for uncertainty and investor disagreement about a stock. Because according to D'Avolio (2002) when there is more disagreement about a stock should increase short interest regardless of whether there is short arbitrage of the accrual anomaly. Therefore they use following controls for uncertainty: Analyst following: Analyst following can affect the accuracy of market perceptions and susceptibility to investor misperceptions (which can potentially overwhelm the arbitrage capital of investors who are willing to sell short). Residual standard deviation and leverage: They are used as proxies for the risk of arbitrage, which should increase return asymmetry. Book-to-market: since there is likely to be more disagreement about growth firms than mature firms. They also use a dummy variable for negative profit of the firm.

Aitken, etal. (1998) uses short sales data on the Australian Stock Exchange (ASX) to confirm that short sales are bad news, and to precisely measure the negative cumulative abnormal return on both a fifteen-minute interval and transaction-to-transaction basis. It is concluded that in a market in which short sales are fully transparent moments after execution, they are almost instantaneously bad news. The main contribution of the paper is first studying a market setting in which information on short trades is transparent just after execution (ASX) (Short sale data are in real time), second analyzing price behavior utilizing abnormal returns based on precisely matched trades following short selling activity on an intraday basis and third differentiating between short trades executed through market orders and limit orders. Regression analysis is also carried out to determine under what conditions short trades are more (or less) likely to be informative.

In Diamond and Verrechia (1987) model, the costs associated with short selling will squeeze liquidity traders out of such order flow, therefore short orders are more informative than regular sell orders. Hence, short sales will help price adjustment at the time such information is made public. In ASX, short selling is made public shortly after the time of trade, therefore all market participants can observe short sales, and, as a result, negative abnormal returns are expected to be associated with short trades. (In U.S. markets the announcement of past short position in a stock is made up to one month later.)

Figlewski and Webb (1993) argue that short selling in options-listed stocks is less likely to be informative, because informed traders utilize the options market where the costs of shorting are lower. They find that stocks with traded options are less likely to be associated with negative abnormal returns following the short sale.

Chen and Singal (2003) find evidence for another explanation of weekend effect. Weekend effect which is remained an unexplained anomaly is defined as higher return on Fridays and lower return on Mondays. In the paper, the role of speculative short sales are examined and finds evidence that speculative short sellers cover their positions on Friday to avoid the risk associated with the inability of monitoring the stock market during non-trading days and then their reopen their position on Mondays. This trading behavior partly explains the weekend effect. By covering their position on Friday, the stocks prices go up and then by reopening their positions on Monday the stocks prices are moved down. The paper studies the relation between relative short interest and the weekend effect (Friday's return minus Monday's return). The authors reason that short sellers are willing to buy put options if the stock has actively traded options instead of short sales because short sales are risky positions. Therefore there should be a negative relation between the number of put option traded and the weekend effector in other words, the higher the put option is traded the lower is the weekend effect. The results show that stocks with listed options have a significantly smaller weekend effect.

Asquith et al. (2005) investigate the relation between the short interest and the future abnormal return. Stocks with high level of short interest ratios and low level of institutional ownership are considered to be short sale constrained, because the demand is high (level of short interest) while the supply (level of institutional ownership) is low. For stock which short sale constraint is biding the hypothesis is that they will underperform the market. They use portfolio construction approach. First all the stocks were ranked based on short interest ratios and each portfolio is then ranked based on institutional ownership. They find that those stocks in top decile short interest portfolio (highly shored) and in the lowest third institutional ownership underperform relative to a four-factor model by 215 basis point per month on an EW basis. In the paper short selling are classified to short selling for arbitrage or overvaluation reason. Then one type of arbitrage short, convertible arbitrage is investigated. As a proxy outstanding convertible bond is used. The findings show that convertible bond arbitrage is a major reason for high short interest. The paper shows that arbitrage shorts do not underperform much.

Desai et al. (2002) study the relation between the level of short interest and the following abnormal return in NASDAQ. They find that firms with higher level of short interest experience negative abnormal return. Calendar time portfolio approach is used. Monthly equally weighted portfolio excess return of stocks with at least 2.5% short interest is regressed on Fama French and Carhart factors and results in an alpha of -0.76 percent per month. The authors also form portfolios of firms with short interest in the 90th and 95th percentile or higher in the previous month. The portfolios are rebalanced monthly to only keep the firms with short interest above 90th and 95th percentile. The results still shows a negative significant relation between short interest and stock return. So Desai et al. (2002) conclude that short selling is a bearish signal. The results for the value weighted analysis show that abnormal return is less negative, but still relatively large and significant.

According to Dechow et al. (2001) Short sellers target firms with low fundamental-to-price such as cash flow to price, earnings to price, book to market and value to market. Short sellers use these ratios to identify overpriced stocks and will cover their position when prices decline. The firms are sorted each year into six categories based on the magnitude of the short position in the stock. For each category, the mean one-year-ahead abnormal return is calculated for each year. The results show a negative relation between the short sale and future return. The other method used in the paper is constructing portfolios based on fundamental to price. 10 portfolios are constructed; portfolio contains stocks with the lowest fundamental to price while portfolio 10 includes stocks with the highest fundamental to price. Abnormal return is the most negative for portfolio 1 and 2 and increases monotonically as we go from portfolio 1 to 10. Then in each portfolio of fundamentals to price, the stocks are categorized to highly shorted and lightly shorted. The results show that not all stocks with low fundamentals to price ratios are heavily shorted. The authors state that there are two reasons why some of stocks with low fundamental to price ratios are not heavily shorted. The first reason is the high transaction cost of short selling and the other reason might be that short sellers have additional information that the stock is not overpriced. The results indicate that short sellers are attracted to low fundamentals to price ratio stocks but avoid stocks with high transaction costs (larger stocks, stocks with low institutional ownership or low dividend yield). The results also support that short sellers have additional information about a stock that has low fundamental to price ratio but not overpriced. For instance firms with low short positions have significantly larger price increases relative to firms with high short positions.

Drake et al. (2015) study the role of short sellers in impounding the future earnings information in current stock prices. There is a concern of reverse causality, because short sellers might select firms with high future earnings which results in a selection bias. To help control for the selection bias, the paper uses Heckman selection model. In the first stage, they run a probit regression with probability of short selling as the dependent variable. The exogenous independent variable considered in the first stage is a variable indicating whether the firm has outstanding convertible debt. We expect that firms with high convertible debt are highly shorted versus firms without convertible debt. But convertible debt will not impact the relation between the current return and future earnings. Then Inverse Mills ratio is calculated and included in next models to control for selection bias.

There are studies that investigate the role of smart investors in related firms. An example is a paper recently working by Akbas et al. (2016). The paper studies the information flow between peer stocks and the effect of short sellers trading on peer stocks' future share prices. They show that higher short interest in a stock is significantly and positively associated with future returns and earnings surprises of the closest competitor. Therefore, the study provides evidence that informed trading not only affects the stock's own prices but also has an impact on the future prices on of the competitors. The former effect is negative while the latter is positive. The main hypothesis in the paper is that short interest contains information about peer stocks. The result support the hypothesis and is robust to various control variables such as the firm's own short interest, stock price momentum, size, institutional ownership, book- to-market. The authors find out that industry lead-lag effects, industry momentum and competitors past return and trading activity do not explain the findings. In another test, longer horizons return (12 month) is regressed on the previous variables. The result is similar suggesting that the effect of short selling on the stock return of peers does not reverse within a few months, therefore the information of short sellers is related to firm fundamentals and the return effect is based on information. The authors also test the relationship between short interest and the earnings surprises in the competing firms. They repeat the regression using quarterly regressions, where the dependent variable is the quarterly earnings surprises. They use standardized unexpected earnings as a measure of earnings surprise. The results show that the effect of competing firm short interest is positive and significant but one this of the effect of firm's own short interest (which is negative effect). So the results suggest that short sellers trade peer stocks because they are informed rather than being short term speculative.

In another study, Alldredge et al. (2014) show that insiders make profit by attentive trading based on public information. The public information used in the paper is the information regarding the customers and suppliers which is available for public. Since insiders are more attentive to their firms customers information they are able to make profit based on that information. The paper finds that insiders of the firms that sell a large amount of their product to principal customers make more profit from stock sales (not purchase) comparing to insiders in non-linked firms. The insiders in linked firms make profit by monitoring the performance of the firm's principal customers and the customers' past return predict the abnormal return of the insiders following the sales.

To test the hypothesis the authors uses two different approaches. First, they compare insider trading returns at firms with economically linked customers to insider trading return in firms with no economic links. The paper finds NYSE size-adjusted decile one month CARs following insider trades. To be consistent with the hypothesis one would expect that CARs following the insider sales be negative. The results show that CARs following the insider sales is more negative for the linked firms versus non-linked firms. The next methodology is multivariate approach. In this method excess one month return following trade months is regressed on the equal weighted market return and a set of control variables (firm's market value, book to market and prior firm's stock return). The authors also run the regressions using only trades at linked suppliers that were done in the first year of the relationship; in this way they want to recognize whether insiders use their private information or public information to make profit. Because, during the first year of relationship, the link might not have yet been disclosed to public. The regression results show that there is no significant negative abnormal return following insiders' sales or purchases during the first year of link. However, the results show that for insiders' sales for linked firms with negative customer lagged return the abnormal return following the sales is negative and significant. The result is not significant for insider's purchases.

3. Data Analysis

3.1. Customer Supplier Data

The data are obtained from several sources. Regulation SFAS No. 131 requires firms to report the identity of customers representing more than 10% of their total sales in the financial reports issued to shareholders. I extract the identity of the firm's principal customers from the Compustat segment files. My customer data cover the period between 1981 and 2015. For each firm I determine whether the customer is another company listed on the CRSP and I assign it the corresponding CRSP permno number. However, 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, I use a Fuzzy matching algorithm. First I generate a list of potential matches to the customer name, I assign a score to each match and I then visually hand-match the customer to the corresponding permno number by looking at the firm's name, segment, and industry information.[19] I am very conservative in matching procedure and firm identifiers to make sure that customers are matched to the appropriate stock returns and financial information. Customers for which I could not identify a unique match are excluded from the sample. Following Cohen and Frazzini (2008), to ensure that the firm–customer relations are known before the returns they are used to explain, I 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. Table 1 shows summary statistics for the sample. In Panel A, I report the statistics for the number of suppliers and customers in my sample. Panel A also shows that on average 76% of firm–customer relations

[19] I am thankful to Andrea Frazzini for providing the clean customer-supplier links from 1981 till 2005. I was able to validate the results of my matching algorithm to Cohen and Frazzini (2008).

are between firms in different industries. Thus, as mentioned in Cohen and Frazzini (2008), the stock return predictability is mostly related to assets in different industries as opposed to securities within the same industry. From summary statistics in Panel B, we also see that number of customers per firm is on average 1.66 with maximum of 21 customers per firm.

3.2. Short Interest Data and Related Data

My empirical tests examine the ability of short sellers to predict low return on the basis of public information about related firms' (customers' or suppliers') financial health. Monthly short interest data are obtained from the New York Stock Exchange (NYSE) and NASDAQ[20] for the period of 1988 to 2015. Short interest shows the open short positions of stocks with settlements on the last business day on or before the 15th of each month. Following Asquith et al. (2005), I calculate monthly raw short interest for each firm, as the percent of total shares outstanding in that month. Shares outstanding data are obtained from CRSP. The final sample consists of all NYSE or NASDAQ-listed common stocks for which monthly short interest reports are available over the period from 1988 to 2015. Table 2 Panel A. shows the summary statistics for raw short interest in my sample. The average short interest in the universe is 2.16%, while suppliers' short interest is 2.32% and customers' short interest is 2.50%. These statistics shows that short interest is on average higher in suppliers. This result is consistent with Boehmer et al. (2008). They find that relative short measure has opposite correlation to the market cap. They find that large stocks have light shorting compared to small stocks when we scale the shorting measure by the number of

[20] I am thankful to Honghui Chen for providing the monthly short interest data for NASDAQ up to 2003 (Chen et al. 2003).

shares outstanding. Although smaller stocks are more expensive to short (Geczy et al. 2002)[21], the relative short interest in suppliers is close to customers in terms of statistics, this might be because short sellers have more information advantage in small stocks. The higher informational advantage comes from the fact that smaller stocks have relative shortage of research coverage and other readily available sources of information. The time series statistics of short interest in suppliers versus customers is shown in Figure 2. We can see a smooth increase in level of short interest in all firms, suppliers and customers and then there is a drop in short interest starting the end of year 2008 when the financial crisis begins. The reason for the sudden drop is the short sales regulations issued during the financial crisis of 2008. In September 2008, the U.S. Securities and Exchange Commission (SEC) issued an emergency order that temporarily banned most short sales in nearly 1,000 financial stocks (Boehmer et al. 2013, Kolasinski, et.al. 2013). As a result of the short sale ban, the cost of borrowing stock increased dramatically in the period of the Emergency Order. Therefore shorting activity dropped by approximately 32%, 26% and 35% respectively for all firms in universe, customer firms and supplier firms.

In addition to raw short interest data, I also calculate a measure of abnormal short interest. I follow Karpoff et al. (2010) for measuring monthly abnormal short interest. For firm *i* in month *t*, abnormal short interest is calculated as follows:

$$ABSI_{it} = SI_{it} - E(SI_{it}) \tag{2.1}$$

[21] In this paper, the return predictability that I find does not account for any potential costs of shorting.

Where SI_{it} is raw short interest and $E(SI_{it})$ is the expected short interest controls for the firm's market capitalization, book-to-market ratio, past stock performance, and industry. Following Karpoff et al. (2010), I first sort all stocks (excluding customer and supplier firms in my sample) based on size, book-to-market and momentum (all measured at the end of the previous month). 27 portfolios are then constructed based on all three independent sorts. Next, at the beginning of each month, each stock is assigned to one of 27 portfolios. Each of the 27 portfolios is next partitioned into industry groups using two-digit SIC codes. I run the following multivariate regression to get the $E(SI_{it})$.

$$SI_{it} = \sum_{j=low}^{med} s_{jt} Size_{ijt} + \sum_{j=low}^{med} b_{jt} BM_{ijt} + \sum_{j=low}^{med} m_{jt} Mom_{ijt} + \sum_{s=1}^{S} d_{st} Ind_{ist} + \varepsilon_{it} \qquad (2.2)$$

The independent variables are dummies that define the 27 benchmark portfolios. For instance, $Size_{i,med,t}$ =1 if firm *i* is assigned to the portfolio with the medium market capitalization in month t. That means for this stock at month t the two other dummies related to size are zero. In other words, $Size_{i,low,t} = 0$ and $Size_{i,high,t} = 0$. Similarly, industry dummy Ind_{ist} equal one if firm i belongs to industry s in month *t* and zero otherwise. The fitted values from each monthly cross-sectional regression are used to estimate the expected short interest for each firm in each month ($E(SI_{it})$), which is used to calculate the abnormal short interest $ABSI_{it} = SI_{it} - E(SI_{it})$. Table 2. Panel B. Shows the coefficient of the regression in equation 2 and Panel C. shows the summary statistics of abnormal short interest for supplier and customer.

I also require the availability of at least one month of past return data from CRSP. I control for size which is the market value of equity calculated as the previous month-end number of shares outstanding times share price. I control for lagged returns of each stock, MOM and its customers, MOM. MOM is the cumulative return over the past twelve months and captures the momentum effect documented by Jegadeesh and Titman (1993). Table 3 shows the correlation matrix. The correlation between supplier's short interest and customer's short interest is 0.12. The relatively small positive correlation suggests that the two measures capture different information. Customer relative short interest is negatively correlated with customer's size and the customer firm's own future return. However, the magnitude of correlation between customer short and its own future return is very small (-0.006). We cannot see any significant correlation between customer short interest and supplier firm's future return, meaning that customer's short does not predict suppliers' return. On the other hand, looking at the correlation between supplier's short and the firm's own future return, we see a negative correlation of (-0.017). Supplier's short, however is positively correlated with supplier size and customer size. In the meantime, there is a negative and significant correlation between supplier short and customer's return, which means suppliers' short contains information about the future return of customers. I will confirm these results in the analysis section with running multiple regressions and portfolio construction.

For data analysis, first, I replicate Cohen and Frazzini (2008), and I find the evidence for return predictability along the supply chain. Table 4 shows the results of return predictability for the full sample. The results show that investors underreact to firm specific information. Investors fail to consider the information about the firms that are economically linked to the main firm and as a result the predictability of return exists across assets. In particular, stock prices underreact to negative (positive) news involving related firms, and in turn generate negative (positive) subsequent price drift. To test this hypothesis, I follow Cohen and Frazzini (2008). Particularly, at the beginning of each month I rank all suppliers in an ascending order according to abnormal return of their customers in the previous month. If a supplier has more than one customer, then equally weighted or value weighted abnormal return is considered. Then construct quintile portfolios of suppliers. The top quintile contains the suppliers whose customers have had best performance in the previous month and the bottom in the quintile is the portfolio that contains the suppliers whose customers have had the poorest performance in the previous month. If the market is inefficient then we expect predictable returns, in other words, the negative shock to firms will affect their related firms with a lag. I report returns in month t of portfolios formed by sorting on customer returns in month t−1. The first row 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 non-missing customer return and non-missing stock price at the end of the previous month. 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 1.07% per month (t-statistic = 6.68). 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 0.96% per month (t-statistic = 5.97). The results show that even after controlling for past returns, high (low) customer momentum stocks earn high (low) subsequent (risk-adjusted) returns 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.[22]

The delayed response of stock prices to new information when bad news arrives can provide a strong incentive for short sellers to acquire information about firm's customers and to profit by short-selling the firm's stock after negative shock to customers. Therefore, in the next section of the study I test whether short sellers are attentive to the negative information about related firms and are able to profit from it. Following Asquith et al. (2005), I calculate short interest as the short position in a given month scaled by the number of shares outstanding reported on CRSP. With annual data, Dechow et al. (2001) show that changes in short interest is positively related to changes in prices. They suggest that short sellers take positions in stocks that experience price run-ups and then cover as prices decline. Diether et al. (2008) use daily data to show that short sellers are also contrarians. Therefore, I need to control for supplier's return in the preceding month to separate out the effect of firms with high return on the change in relative short interest.

4. Empirical Results

4.1. Firm short interest and future return of related firm

I investigate short interest level along the supply chain to determine whether short sellers incorporate supply chain information into their trading decisions. Specifically, I test the correlation between supplier's (customer's) short interest and future return or earnings surprise of its

[22] The results for all quintiles are available upon request. In these tables, however, I just reported the alpha from Long short strategy.

customers (suppliers). [23]

4.1.1. Portfolio Approach

First, I use portfolio sorts in order to test the main hypotheses of my paper: the short interest contains information about related firms in its supply chain. My main hypothesis has two parts; first I test whether firms' short interest contain information about the future return of the firm's customers and second I test whether it has information about the future return of the firm's suppliers. In Table 5, I present portfolio sorts as a precursor to my main regression analysis. To study part one of the main hypothesis or the relation between customer firm's short interest and future return of supplier firm, at the beginning of each month, I first group the sample into customer firm short interest (CUSS) quintiles and then rank them based on firms' average short interest (SUPS) within each customer short interest (CUSS) quintile. All sorts are independent. I report time series averages of equally weighted monthly portfolio of supplier's raw returns and alphas obtained from Fama French three factor model and Carhart (1997) four-factor model. I skip one month between the portfolio formation period and the holding period. The results are shown in Table 5 Panel A and Panel B. Panel B shows the difference in risk adjusted return between the highest and lowest supplier short quantiles (on the left side) and the difference in risk adjusted return between the highest and lowest supplier short quantiles (on the right side). The negative significant correlation between supplier short interest (SUPS) and supplier future return (controlling for customer short interest) which is found in Panel A and B is consistent with previous literature that firm's short interest is negatively related own firm's future one month return. The

[23] I conducted the empirical analysis for both measure of short interest, raw short interest and abnormal short interest. However, I didn't find any interesting results for abnormal short interest based on Karpoff et al. (2010), therefore from now on by short interest I means raw short interest which is as a percentage of shares outstanding.

results in Panel A show that heavily shorted suppliers (SUPS5) significantly underperform lightly shorted suppliers (SUPS1) by 0.90% to 1.53% raw return (0.96% to 1.65% risk adjusted return) per month with t-stat ranges from 2.76 to 4.65 (t-stat ranges from 3.10 to 5.27 for risk adjusted return). My result, however, doesn't show a significant relationship between firm's future returns and the short interest in its customer. So customer firm's short interest doesn't contain any information about the future return of the suppliers. Results show only a positive and non-significant relationship between firm's future returns and the short interest in its customer in all quintiles. The magnitude of raw return (risk adjusted return) between the heavily shorted customers and lightly shorted customers ranges from 0.25% to 0.38% (0.13% to 0.26%) but t-stat is not significant in any quantile.

Next, I use portfolio approach to test whether supplier short interest contain information about the future return of customer firms. Following the same methodology, each month, I first group the sample into supplier firm short interest (SUPS) quintiles and then rank them based on customer firms' average short interest (CUSS) within each supplier short interest (SUPS) quintile. All sorts are independent. The results are shown in Table 5 Panel B. The question is whether there is information in supplier short interest about the future return of customer firms, therefore, I report time series averages of equally weighted monthly portfolio returns of customers. I skip a month between the portfolio formation period and the holding period. My result shows a negative significant relationship between customer firm's future returns and the short interest in its supplier. Panel C shows that in quantile 5 (CUSS5), heavily shorted suppliers underperform lightly shorted suppliers by 0.38% monthly raw return with t-stat of 1.73. So supplier firm's short interest contains information about the future return of the customers. But the informativeness of supplier short interest about the future return of customer happens in the quantile where customers are heavily shorted, therefore one explanation of the result might be short sale constraint in customer firms. I will test this hypothesis in section IV. Panel D shows the risk adjusted abnormal returns for customer firms for the difference between heavily and lightly shorted suppliers and customers. Controlling for market factor, magnitude of alpha increases slightly from 0.38% (t-stat=1.73) to 0.44% (t-stat=1.96). When we include Fama French three factors, the magnitude of alpha does not change significantly and is 0.35% (with t-stat of 1.67). However, adjusting for Carhart momentum factor, the magnitude of abnormal return decreases to 0.20% and is not significant anymore.[24] Panel C and D show one more interesting result. Unlike suppliers, I see no significant correlation between short interest and future return for customer firms. An exception is the risk adjusted return for the quintile where suppliers are moderately shorted (quantile 3: SUPS3) where the magnitude of risk adjusted return from shorting the customers that are heavily shorted and buying the customers that are lightly shorted is 0.45% with t-stat equal to 1.96. In other quantiles both in Panel C and D, there is no significant relation between the short interest and the future one month return for customer firms. Customer firms are very large firms so one reason that we can't find this negative correlation might be the size. However, in untabulated results, I find the controlling for size there is no relation between customer short interest and customer on month future return, suggesting that size is not the reason. Panel E shows the number of links in each portfolio. Portfolios are balanced and there are on average 1100 firms in each portfolio.

[24] I repeated the portfolio analysis for two month lagged short interest instead of one month and find slightly stronger results. The results are available in Appendix I.

4.1.2. Regression Analysis

Table 6 to 9 show the results of regression analysis. I test whether short interest contains information about economically related firms. Specifically, I regress a firm's future returns on the short interest in its customer or supplier, controlling for characteristics that might differentiate the two firms. To avoid potential bid-ask bounce effects on the estimates, I skip one month between dependent variable and explanatory variables in all my regression tests. The main variable of interest in all regression is firm short interest (supplier's or customer's), and I test how it is correlated to the related firm's future return at different horizons.

First, I test whether supplier firm's short interests contain information about the one month future return of customer firms. Table 6 shows the results. Model 1 is similar to my portfolio approach, since I only include supplier and customer short interest in the model. Other specifications (Model 2 to 6) control for characteristics of supplier and customer firms. For control variables, I use the log of market capitalization (SIZE), the log of book to market ratio (BM), institutional ownership (IO) and past twelve month cumulative return (MOM). The reason for including the past 12-month cumulative return for both customer and supplier is that price reaction of an easy-to-analyze firm may lead the price reaction of a complicated firm, when both are subject to a common shock (Cohen and Lou 2012). If a firm is a firm that is easy to analyze, then I could find a relationship between a firm's future return and the related firm (either customer or supplier) short interest just because short interest and past returns are correlated for the related firm (Diether et al. 2009). This reasoning is also addressed by Akbas et al. (2016). Model 5 and 6 excludes customer short interest to make sure the results are not affected by a potential multicollinearity problem. The results in Table 6 show that, a customer's future one-month return is negatively and significantly related to supplier firm short interest. The coefficients for supplier short interest in all models are negative and significant and range from -0.027 to -0.036 with t-stat ranging from -4.45 to -5.31. The result shows that supplier short interest contains information about the future return of customer firms because the higher the short interest in supplier the lower is the one-month future return of customer firm. In other words, one percent increase in supplier firm's short interest is associated with approximately 0.03% decrease in the customer firm's future one month return. Unlike the portfolio result we see a negative correlation between customer short interest and customer one month future return. The magnitude of the predictive power of supplier short interest about the customer firm's future one month return is more than half of the magnitude of the predicting power of customer's own short interest.

Looking at the customer firm characteristics as control variables, we see that the coefficient of SIZE if negative but not significant. BM and MOM are positively and significantly related to the firm's future return and the coefficient of IO is also positive but insignificant. Examining the characteristics of supplier firm as control variables in Model 4 to 6, we can notice that supplier size is negatively and significantly related to future return of customer firms. The other variables are positive but insignificant except for the last model where I exclude the customer firms' characteristics from the model. Overall, the results in his table show that after controlling for firm characteristics, the economic magnitude and significance of the coefficient of supplier short interest doesn't change significantly.

Table 6 shows that supplier short sale is informative about the customer's one month future return. Next, I examine whether the negative relation lasts for longer return horizons. Specifically

I test the relation between supplier short interest and customer firm's future twelve month cumulative return. I repeat the analysis for Table 6 but this time the dependent variable is customer firm's future twelve month cumulative return. Instead of customer's future one month return. Considering the Longer horizons helps to determine whether the negative relation between supplier short interest and customer future return is transient or not. If the negative relation reverses when we consider longer return horizon, it would indicate that the return effect is likely not based on information and is a temporary effect. The results are shown in Table 7. The coefficient for supplier short remains negative and significant in all model specifications. However, the magnitude of the coefficient is much higher when we consider the longer return horizon as the dependent variable. The coefficient for supplier short ranges from -0.327 to -0.510 with t-stat ranging from -4.52 to -5.31. The results show that the return effect is based on information and does not reverse after 12 month. I can conclude that supplier short interest is economically important, both in an absolute sense and relative to the well-established short-interest effect on customer's future returns.

Next, I study whether customer short interest has information about the future return of supplier firms. The result of regression analysis is shown in Table 8. The results show that there is no significant relation between customer short interest and future return of supplier firm. However, I see a negative and significant relation between supplier short and supplier's own future ne month return. When the dependent variable is longer return horizon (Table 9) I can see that coefficient of Customer short interest (CUSS) becomes positive and significant.

4.2. Firm Short Interest and Future Earnings Surprise of Related Firm

Zhu (2014) studies whether market underreact to customer earnings announcement as a result of investors' inattention. Therefore, in this section, I estimate the cross-firm effects of short interest on earnings surprises. Short sellers are known to be informed about upcoming earnings announcements (Christophe et al. 2004; Akbas et al. 2013), therefore I expect changes in firms' short interest to reflect the information about the future earnings of related firms. I repeat the main regression analysis where quarterly earnings surprises are the dependent variables. I construct earnings surprises from quarterly earnings announcements from Compustat. I use standardized unexpected earnings (SUE) as a proxy for earnings surprises. Following Foster et al. (1984) and Chan et al. (1996), I define SUE in quarter q as:

$$SUE_q = {(EPS_q - E[EPS_q])}/{\sigma_q} \qquad (2.3)$$

Where q is the quarter, EPSq are the most recent quarterly earnings per share, E[EPSq] are expected earnings per share, and σq is the standard deviation of unexpected earnings (EPSq – E[EPSq]) over the preceding eight quarters. Similar to the previous section, I first use the portfolio approach and then apply multivariate regression analysis.

4.2.1. Portfolio Approach

First, I use portfolio sorts in order to test whether the short interest contains information about the earnings of related firms in its supply chain. In Table 10, I present portfolio sorts. To study the relation between customer firm's short interest and future earnings of supplier firm, at the beginning of each month, I first group the sample into customer firm short interest (CUSS) quintiles and then rank them based on firms' average short interest (SUPS) within each customer short interest (CUSS) quintile. All sorts are independent. I report time series averages of equally weighted quarterly portfolio of supplier's earnings surprises. I skip one month between the portfolio formation period and the holding period. The results are shown in Table 10 Panel A. The negative significant correlation between supplier short interest (SUPS) and supplier future earnings (controlling for customer short interest) which is found in Panel A is consistent with previous literature that firm's short interest is negatively related own firm's future earnings surprise. The results in Panel A show that heavily shorted suppliers (SUPS5) significantly underperform lightly shorted suppliers (SUPS1). My result, however, doesn't show a significant relationship between firm's future earnings surprise and the short interest in its customer. So customer firm's short interest doesn't contain any information about the future earnings of the suppliers. Results show a negative and non- significant relationship between firm's future earnings surprise and the short interest in its customer in most quintiles.

Next, I use portfolio approach to test whether supplier short interest contain information about the future earnings surprise of customer firms. Following the same methodology, each month, I first group the sample into supplier firm short interest (SUPS) quintiles and then rank them based on customer firms' average short interest (CUSS) within each supplier short interest (SUPS) quintile. All sorts are independent. The results are shown in Table 10 Panel B. The question is whether there is information in supplier short interest about the future earnings surprise of customer firms, therefore, I report time series averages of equally weighted quarterly portfolio earnings surprise of customers. I skip a month between the portfolio formation period and the holding period. My result shows a negative significant relationship between customer firm's earnings surprise and the short interest in its supplier. Panel B shows that in quantile 5 (CUSS5), heavily shorted suppliers underperform lightly shorted suppliers by 0.15% quarterly earnings surprise with t-stat of -1.78. So supplier firm's short interest contains information about the future earnings of the customers. But the informativeness of supplier short interest about the future earnings of customer happens in the quantile where customers are heavily shorted, this is again consistent with the previous section where I consider the stock return as variable of interest instead of earnings surprise. Therefore one explanation of the result might be short sale constraint in customer firms. In section V, I find evidence that one reason for short sellers to short suppliers is customer firms' short sale constraint. Again, Panel B shows one more interesting result. Unlike suppliers, we see no significant correlation between short interest and future earnings surprise for customer firms.

4.2.2. Regression Analysis

Table 11 and 12 show the results of regression analysis. I test whether short interest contains information about the earnings of economically related firms. Specifically, I regress a firm's future earnings surprise on the short interest in its customer or supplier, controlling for characteristics that might differentiate the two firms. To avoid potential bid-ask bounce effects on the estimates, I skip one month between dependent variable and explanatory variables in all my regression tests. The main variable of interest in all regression is firm short interest (supplier's or customer's), and I test how it is correlated to the related firm's future earnings surprise.

First, I test whether supplier firm's short interests contain information about the next quarter earnings surprise of customer firms. Table 11 shows the results. Model 1 is similar to my portfolio approach, since I only include supplier and customer short interest in the model. Other specifications (Model 2 to 6) control for characteristics of supplier and customer firms. For control variables, I use the log of market capitalization (SIZE), the log of book to market ratio (BM), institutional ownership (IO) and one quarter lagged surprise for both supplier and customer (lag SUE). The reason for including past earnings surprise is to make sure the results are not driven by the earnings momentum effect (Chan et al. 1996). Model 5 and 6 excludes customer short interest to make sure the results are not affected by a potential multicollinearity problem. The results in Table 11 show that, a customer's future earnings surprise is negatively and significantly related to supplier firm short interest. The coefficients for supplier short interest in all models except model 1 are negative and significant and range from -0.027 to -0.036 with t-stat ranging from -1.87 to -2.74. The result shows that supplier short interest contains information about the future earnings of customer firms because the higher the short interest in supplier the lower is the next quarter earnings surprise of customer firm. In other words, one percent increase in supplier firm's short interest is associated with approximately 0.003% decrease in the customer firm's future earnings surprise. [25]

Looking at the customer firm characteristics as control variables, we see that the coefficient of SIZE is positive but and significant at 1% level. BM and IO are not significant and one quarter lagged earnings surprise of customer firms is positively and significantly related to the next quarter earnings surprise of customer firm. Examining the characteristics of supplier firm as control variables in Model 4 to 6, we can notice that supplier size and lagged surprise is positively and

[25] Considering the information content of two month lagged short interest the coefficient of the two month lagged short interest is around -0.005 and t-value of -3.33.

significantly related to future earnings surprise of customer firms. The other variables are insignificant. Overall, the results in his table show that after controlling for firm characteristics, the economic magnitude and significance of the coefficient of supplier short interest doesn't change significantly.

Next, I study whether customer short interest has information about the earnings of supplier firms in the next quarter. The result of regression analysis is shown in Table 12. The results show that there is a significant negative relation between customer short interest and future earnings surprise of supplier firm. The results in Table 12 show that, a supplier's future earnings surprise is negatively and significantly related to customer firm short interest. The coefficients for customer short interest in all models are negative and significant and range from -0.007 to -0.014 with t-stat ranging from -2.03 to -2.74. The result shows that customer short interest contains information about the future earnings of supplier firms because the higher the short interest in customer the lower is the next quarter earnings surprise of supplier firm. In other words, one percent increase in customer firm's short interest is associated with approximately 0.008% decrease in the supplier firm's future earnings surprise.[26] In addition, consistent with previous literature, there is a negative and significant relation between supplier short and supplier's own earnings surprise.

4.3. Short Sellers' Incentive to Short Suppliers or Customers:

4.3.1. Short Sale Constraint

One plausible channel that explains the information content of short interest for related firms' stocks along the supply chain would be short sale constraints. The negative relationship in

[26] Considering the information content of two month lagged short interest the coefficient of the two month lagged short interest for customer firm is around -0.01 and t-value of -1.79.

Table 5 Panel B (Table 10 Panel B) between firm short interest and future returns (earnings surprise) of customer firm is driven mainly by stocks with the highest customer's short interest. Thus a firm's short interest predicts future stocks returns of the firm's customers mostly when the level of short interest in the customer firm is high. A possible explanation would be when short sellers have negative information about a firm they start shorting the firm's stock until short selling constraint binds. Fully exploiting firm-specific private information may be costly when shorting constraints bind. These informed traders, to reduce their trading costs, may then have incentives to strategically make information-based trades in the stocks of supplier firms. In other words, short sellers are generally better informed and they understand the link between firm's and its customers. Hence, if they have negative information about a firm such as Apple, they not only short Apple's stock but also Apple's suppliers.

To test for the effect of short sale constraints, I create a dummy variable that takes one if the customer firm falls in the decile with the highest level of short interest. Then I consider the interaction term between supplier firm short interest and the dummy variable. In particular, I test the following regression:

$$CSUE_{t+1} = a_0 + a_1 SUPs_t + a_2 CUSS_t + a_3 SUPS * CUSS\_High_t + controls + \varepsilon_t \quad (2.4)$$

$CSUE$ is the earnings surprise for customer firm in next quarter. The dummy variable, $CUSS\_High$ proxies for short sale constraints in customer firm. If short sale constraint is the reason for the negative correlation between supplier short interest and future earnings surprise of customer firm, then we expect that the higher the short sale constraint in customer firm, then the stronger is the negative correlation between the two aforementioned variables. For this purpose, I consider the interaction term of supplier's short interest and the dummy whether the customer is highly shorted. The results in Table 13 show that the coefficient of the variable of interest which is the interaction term is negative and significant at 5% level. This means that short sale constraint might be one motivation for short sellers to short the supplier firm when they have pessimistic view about the customer firm.

To test the incentive of short sellers for betting against the customer firms when they have pessimistic views about the supplier firm, I follow the same methodology. Supplier firms are much smaller than customer firms. According to D'Avolio (2002), Chen et al. (2002) and Boehmer and Zhang (2008), smaller firms are considered less liquid and more costly to short. So the smaller the firm the more the short sale constraint binds. Therefore, I test whether short sale constraints in supplier firm again is a motivation for short sellers to short their customers. The following regression is done to test the effect of short sale constraint on the relation between customer short interest and future earnings surprise of supplier firms.

$$SSUE_{t+1} = a_0 + a_1 CUSS_t + a_2 SUPS_t + a_3 CUSS_t * {SUPS_{High}}_t + Controls + \varepsilon_t \tag{2.5}$$

$SSUE$ is the earnings surprise for supplier firm in next quarter. The dummy variable, $SUPS\_High$ proxies for short sale constraints in customer firm. If short sale constraint is the reason for the negative correlation between customer short interest and future earnings surprise of supplier firm, then we expect that the higher the short sale constraint in supplier firm, then the stronger is the negative correlation between the two aforementioned variables. For this purpose, I consider the interaction term of customer's short interest and the dummy whether the supplier is highly shorted. The results in Table 14 show that the coefficient of the variable of interest which is the interaction term is negative and significant at 1% level. This means that short sale constraint might be one motivation for short sellers to short the customer firm when they have pessimistic view about the supplier firm.

4.3.2. Alternative Explanation

Another possible reason for short sellers' incentives to short the supplier firm when they have negative views about the customer firm might be because short sellers have informational advantage in suppliers. According to Boehmer and Zhang (2008), the relative short measure has opposite correlation to the market cap. They find that large stocks have light shorting compared to small stocks when we scale the shorting measure by the number of shares outstanding. Although smaller stocks are more expensive to short (Geczy et al. 2002), the higher relative short interest in suppliers comparing to customers specially during recent years (shown in summary statistics table) might be because short sellers have more information advantage in small stocks. The higher informational advantage comes from the fact that smaller stocks have relative shortage of research coverage and other readily available sources of information.

5. Conclusion

Several papers have shown that shocks to a firm have impacts on economically connected firms (Menzly and Ozbas, 2010, Cohen and Fazzini, 2008, Pandit et al. 2011). In particular, the ripple effect from shocks to customer firms' impacts linked supplier firms with a lag and vice versa. The prevailing explanation for this short-term price inefficiency is investor limited attention. Recently research has suggested that attentive corporate insiders and sell-side analysts who cover both customer and supplier firms incorporate information about the customer-supplier relationship into their supplier trades and estimates more rapidly than their peers (Alldredge and Cicero, 2014, Guan et al. 2014). The focus of this study is to investigate whether short sellers are able to see through the complex customer-supplier relationships and exploit supply-chain information through trading.

The main finding is that short sellers have predictive power; they short suppliers (customers) before the customers' (suppliers') poor performance is realized. In other words, supplier short sale has information about the future return and earning surprise of customers. Moreover, the effect I document predicts returns up to a year ahead, suggesting that the price impact is permanent, not transient. In addition customer short sale has information about the future earnings surprise of supplier firms. These results support the idea that my findings are driven by informed trading. I argue that short sellers may strategically choose to trade a supplier's stock because of short sale constraints and informational advantage. I find consistent results with this explanation.

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Figures and Tables

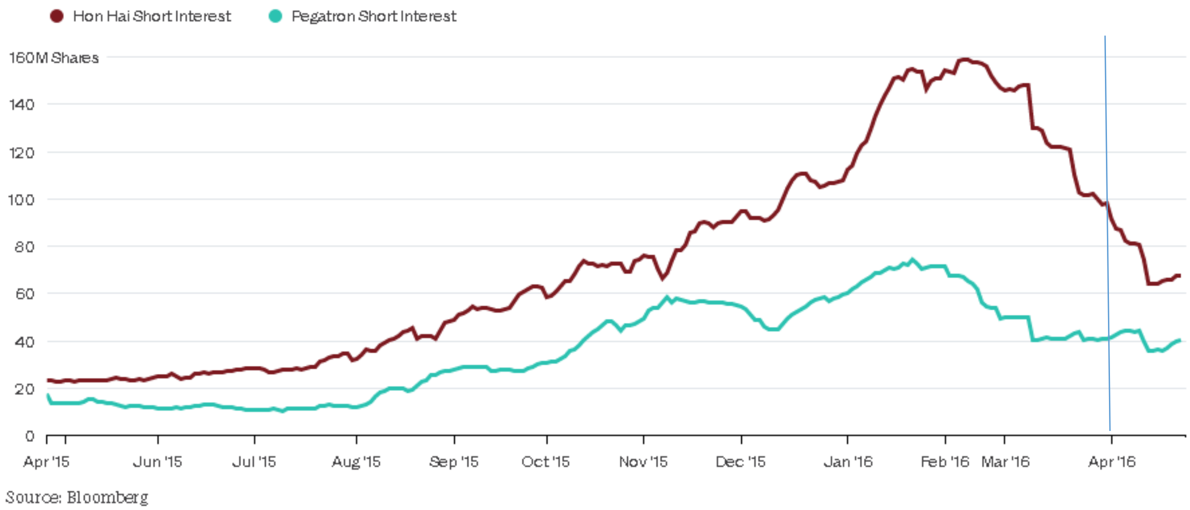

Figure 2.1. Short interest in Apple and its two main suppliers

This figure shows the trend in short interest in Apple's two main supplier firms, Hon Hain and Pegatron. Apple announced negative earnings in April 2016, but short interest in Apple's suppliers reached a crescendo in February.

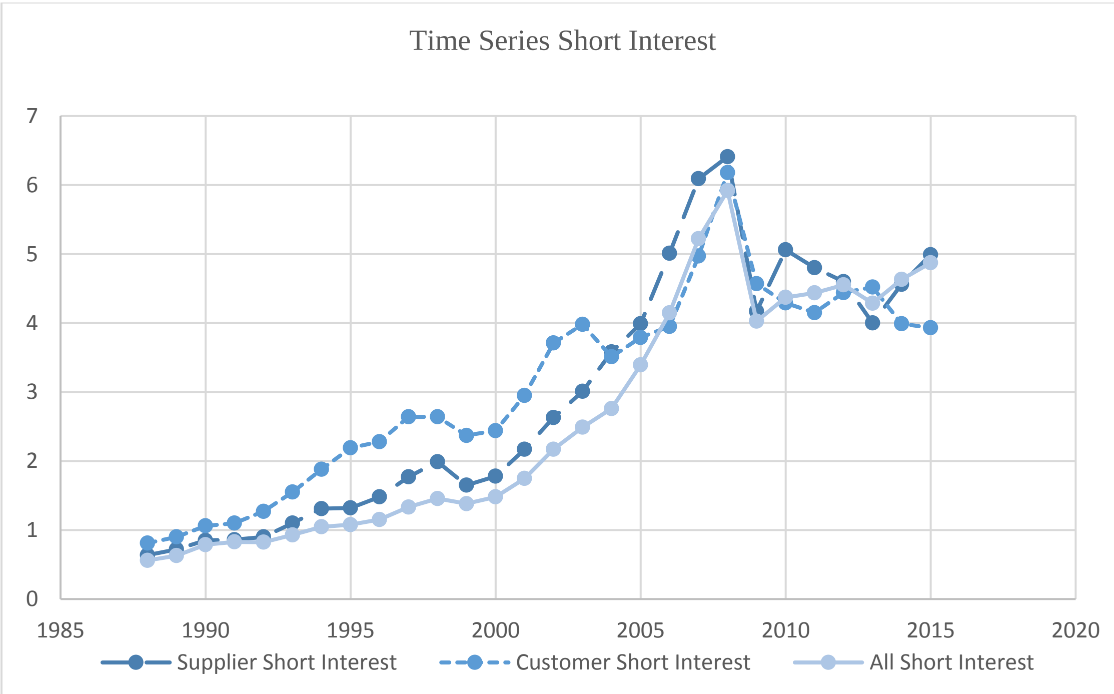

Figure 2.2. Comparing Supplier and Customer firms' average annual short interest

This figure presents time-series averages for short interest. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. Monthly short interest data is defined as the total shares shorted divided by the total shares outstanding measured at the midst of each month.

Table 2.1. Customer-supplier Summary statistics:

This table shows summary statistics as of December of each year. Panel A. shows the time series statistics for link characteristics. Panel B is pooled firm year statistics and Panel C presents time-series averages of statistics for various stock characteristics. SIZE is the market value of equity calculated as the previous month end number of shares outstanding times share price. BM is the ratio of the previous quarter end book value to market value of equity. TURN is the share turnover ratio measured as the number of shares traded divided by the number of shares outstanding in a given month. IO is the institutional ownership, defined as the sum of the holdings of all institutions for each stock in each quarter, divided by the number of shares outstanding. MOM is cumulative return over the past twelve months for a stock. Earnings surprise is standardized unexpected earnings (SUE) defined as difference in Earnings per Share (EPS) before extraordinary items between quarters q and q-4 divided by quarter q-4 end price I apply log transformation for BM and Size.

	Min	Max	Mean	SD	Median
Panel A: Time Series (34 Annual Observations, 1981–2015)					
Number of suppliers in the sample per year	267	1,686	1,158	388	1,244
Number of customers in the sample per year	346	688	555	90	552
% of supplier–customer in the same industry	22.0	29.0	26.0	2.9	23.5
Link duration (years)	1.0	34.0	4.2	3.3	3.0
Panel B :Firms (Pooled Firm-Year Observations)					
Number of customers per firm	1.0	21.0	1.7	1.1	1.0

Panel C : Summary statistics					
	Mean	Median	SD	P1	P99
Supplier BM	0.68	0.54	0.71	-0.40	4.16
Customer BM	0.60	0.49	0.49	-0.49	2.75
Supplier Size ($ Million)	930.40	104.74	2,776.95	1.56	20,140.75
Customer Size ($ Million)	11,309.88	2,335.77	26,584.00	11.48	177,054.00
Supplier Profitability (%)	-1.25	0.76	7.79	-42.79	12.05
Customer Profitability (%)	0.79	1.18	3.31	-17.60	7.27
Supplier MOM (%)	15.02	2.42	72.17	-86.89	357.14
Customer MOM (%)	13.41	10.21	39.21	-73.33	159.13
Supplier Institutional Ownership	0.30	0.20	0.32	0.00	1.08
Customer Institutional Ownership	0.47	0.53	0.33	0.00	1.07
Supplier Return (%)	1.06	0.00	17.15	-43.01	66.67
Customer Return (%)	1.12	0.95	11.37	-28.81	33.45
Supplier SUE (%)	-0.08	0.13	11.91	-59.35	59.75
Customer SUE (%)	-0.05	0.14	4.62	-24.00	21.00

Table 2.2. Short sale statistics (1988-2015)

Panel A. presents time-series averages of cross-sectional summary statistics for short interest. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. Monthly short interest data in Panel A. is defined as the percentage of total shares shorted divided by the total shares outstanding measured at the midst of each month. For each month t, short interest (SI) is regressed on variables that are likely to explain the level of short interest. Short interest (SI) is the number of shares shorted as a percentage of the number of shares outstanding. The table reports the time-series means and t-statistics of the monthly coefficient estimates. For Panel B:

$$SI_{it} = \sum_{j=low}^{med} s_{jt} Size_{ijt} + \sum_{j=low}^{med} b_{jt} BM_{ijt} + \sum_{j=low}^{med} m_{jt} Mom_{ijt} + \sum_{s=1}^{S} d_{st} Ind_{ist} + \varepsilon_{it}$$

Explanatory variables include size, the book-to-market ratio, and momentum, all measured at the beginning of month t. The independent variables are dummy variables. For example, if firm i is assigned to the portfolio with the lowest market capitalization in month t, then $Size_{i,low,t} = 1$, $Size_{i,med,t} = 0$, and $Size_{i,high,t} = 0$. Panel C. reports the coefficient of reports the mean levels of abnormal short interest (ABSI) for customers and suppliers in the sample. Abnormal short interest for each event firm i in month t is the difference between the short interest and the predicted short interest using the coefficients in month t.

$$ABSI_{it} = SI_{it} - E(SI_{it})$$

Panel A. Raw relative short interest

	Mean	Median	STD	P1	P99
Short in universe (%)	2.16	1.36	1.75	0.31	6.34
Customers' Short (%)	2.50	2.41	1.27	0.23	6.41
Suppliers' Short (%)	2.32	1.64	1.88	0.25	6.56

Panel B. Model Used to Calculate Abnormal Short Interest

	$Size_{low}$	$Size_{med}$	BM_{low}	BM_{med}	Mom_{low}	Mom_{med}	*Industry Controls*	*R-squared*
Model to calculate ABSI	-2.19***	-0.10***	0.74***	-0.04***	0.62***	-0.15***	Yes	23.22%
	(-27.15)	(-3.89)	(26.50)	(-4.60)	(17.21)	(-15.01)		

Panel C. Abnormal relative short interest

	Mean	Median	STD	P1	P99
Customers' Short (%)	-1.04	-0.45	1.24	-5.14	0.13
Suppliers' Short (%)	0.03	0.03	0.47	-0.90	0.65

Table 2.3. Correlation matrix.

This table present the correlations among the variables. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. Monthly short interest data is defined as the percentage of total shares shorted divided by the total shares outstanding measured at the midst of each month. SIZE is the market value of equity calculated as the previous month end number of shares outstanding times share price. BM is the ratio of the previous quarter end book value to market value of equity. IO is the institutional ownership, defined as the sum of the holdings of all institutions for each stock in each quarter, divided by the number of shares outstanding. MOM is cumulative return over the past twelve months for a stock. Earnings surprise is standardized unexpected earnings (SUE) defined as difference in Earnings per Share (EPS) before extraordinary items between quarters q and q-4 divided by quarter q-4 end price I apply log transformation for BM and Size.

	Supplier Short	Customer Short	Customer Size	Customer BM	Customer IO	Customer MOM	Supplier CUM	Customer Ret	Supplier Ret	Customer SUE	Supplier SUE	Supplier Size	Supplier BM	Supplier IO
Supplier Short	1.00													
Customer Short	0.13	1.00												
Customer Size	0.10	-0.25	1.00											
Customer BM	-0.07	0.05	-0.44	1.00										
Customer IO	0.16	0.23	0.01	-0.08	1.00									
Customer MOM	-0.04	-0.04	0.11	-0.14	0.01	1.00								
Supplier CUM	0.01	-0.02	0.02	-0.03	0.00	0.24	1.00							
Customer Ret	-0.02	-0.02	0.00	0.02	0.00	0.04	0.00	1.00						
Supplier Ret	-0.02	0.00	0.00	0.01	0.00	0.02	0.01	0.22	1.00					
Customer SUE	-0.01	-0.01	0.04	-0.06	0.00	0.21	0.07	0.10	0.02	1.00				
Supplier SUE	-0.02	-0.01	0.01	-0.01	0.00	0.05	0.10	0.00	0.05	0.07	1.00			
Supplier Size	0.34	0.06	0.18	-0.05	0.11	0.02	0.18	-0.01	-0.01	0.00	0.01	1.00		
Supplier BM	-0.20	-0.01	-0.05	0.16	-0.04	-0.05	-0.18	0.01	0.04	0.00	-0.01	-0.32	1.00	
Supplier IO	0.40	0.11	0.16	-0.05	0.18	-0.02	0.02	-0.01	0.00	0.00	0.00	0.55	-0.09	1.00

Table 2.4. Customer Momentum Strategy, Abnormal Returns

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 equal weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain equal weights. 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 the 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.

Panel A. Customer Momentum Strategy, Abnormal Returns 1981–2015

L/S portfolios	EW - Customer MOM	VW - Customer MOM	EW - Customer MOM	VW - Customer MOM
Alpha	1.07%***	0.85%***	0.96%***	0.83%***
	(6.68)	(3.16)	(5.97)	(3.18)
MKT	-0.06	-0.073	-0.06	-0.07
	-(1.28)	-(0.89)	-(1.26)	-(0.83)
SMB	-0.01	-0.17	-0.01	-0.14
	-(0.12)	-(1.39)	-(0.07)	-(1.16)
HML	0.04	0.097	0.04	0.10
	(0.58)	(0.86)	(0.58)	(0.88)
UMD			0.13***	0.02
			(3.64)	(0.45)

Panel B. Customer Momentum Strategy, Abnormal Returns 1981–2004

L/S portfolios	EW - Customer MOM	VW - Customer MOM	EW - Customer MOM	VW - Customer MOM
Alpha	1.33%***	1.26%***	1.18%***	1.16%**
	(5.92)	(2.31)	(5.07)	(2.17)
MKT	-0.08	-0.061	-0.87	-0.045
	-(1.16)	-(1.04)	-(1.12)	-(0.74)
SMB	-0.01	-0.113	-0.01	-0.115
	-(0.17)	-(1.34)	-(0.14)	-(1.37)
HML	0.00	0.049	0.00	0.069
	(0.09)	(0.55)	(0.11)	(0.77)
UMD			0.16***	0.058
			(3.78)	(1.06)

Table 2.5. Average portfolio returns

This table presents average raw returns (%) for portfolios sorted on monthly short interest, SUPS, and monthly short interest for the customer, CUSS. Monthly short interest data in Panel A. is defined as the percentage of total shares shorted divided by the total shares outstanding measured at the midst of each month. The sample consists of common stocks listed on NASDAQ and NYSE from June 1988 through December 2015. The portfolios are rebalanced every month and I skip a month between portfolio formation and the holding period. Panel A shows the results for average returns of suppliers and Panel B shows the results for average returns of customers. The table also presents the average returns of the high-minus-low short interest, within each short interest group. All sorts are independently conducted. ***, **, and * denote statistical significance level at the 1%, 5%, 10% levels, respectively.

Panel A. Supplier's average raw return

	SUPS1	*SUPS2*	*SUPS3*	*SUPS4*	*SUPS5*	*SUPS5- SUPS1*	*t*
CUSS1	1.23	1.09	1.03	0.72	0.33	-0.90***	-2.83
CUSS 2	1.50	1.23	0.80	1.21	0.57	-0.93***	-2.76
CUSS 3	1.78	1.06	0.97	1.20	0.25	-1.53***	-4.65
CUSS4	1.49	1.67	1.04	1.10	0.62	-0.87***	-2.80
CUSS5	1.56	1.37	1.28	1.10	0.63	-0.93***	-2.82
CUSS5 – CUSS1	0.33	0.28	0.25	0.38	0.30		
t	1.28	1.10	0.95	1.45	1.03		

Panel B. Supplier's average risk adjusted abnormal return

	SUPS5- SUPS1					CUSS5 – CUSS1			
	Excess Return	One Factor Alpha	Three Factor Alpha	Four Factor Alpha		Excess Return	One Factor Alpha	Three Factor Alpha	Four Factor Alpha
CUSS1	-0.90*** (-2.83)	-1.19*** (-3.87)	-1.00*** (-3.30)	-0.96*** (-3.10)	*SUPS1*	0.38 (1.28)	0.25 (1.00)	0.28 (1.10)	0.23 (0.89)
CUSS2	-0.93*** (-2.76)	-1.23*** (-3.83)	-1.16*** (-3.58)	-1.12*** (-3.38)	*SUPS2*	0.28 (1.10)	0.15 (0.59)	0.08 (0.31)	0.13 (0.50)
CUSS3	-1.53*** (-4.65)	-1.88*** (-6.08)	-1.74*** (-5.66)	-1.65*** (-5.27)	*SUPS3*	0.25 (0.95)	0.19 (0.75)	0.17 (0.63)	0.25 (0.92)
CUSS4	-0.87*** (-2.80)	-1.16*** (-3.90)	-1.00*** (-3.38)	-0.98*** (-3.26)	*SUPS4*	0.38 (1.45)	0.23 (0.93)	0.32 (1.27)	0.26 (1.02)
CUSS5	-0.93*** (-2.82)	-1.22*** (-3.84)	-1.14*** (-3.56)	-1.07*** (-3.28)	*SUPS5*	0.30 (1.03)	0.22 (0.77)	0.15 (0.52)	0.13 (0.43)

Panel C. Customer's average raw return

	SUPS1	*SUPS2*	*SUPS3*	*SUPS4*	*SUPS5*	*SUPS5- SUPS1*	*t*
CUSS1	0.92	1.07	1.00	0.94	0.93	0.02	0.10
CUSS 2	1.17	1.09	1.36	1.11	1.10	-0.06	-0.41
CUSS 3	1.14	1.04	1.09	1.04	1.26	0.11	0.57
CUSS4	1.28	1.28	1.13	1.10	1.11	-0.17	-0.88
CUSS5	1.22	1.00	0.73	0.92	0.84	-0.38*	-1.73
CUSS5 – CUSS1	0.31	-0.07	-0.27	-0.02	-0.09		
t	1.24	-0.31	-1.12	-0.09	-0.33		

Panel D. Customer's average risk adjusted abnormal return

	SUPS5- SUPS1					CUSS5 – CUSS1			
	Excess Return	One Factor Alpha	Three Factor Alpha	Four Factor Alpha		Excess Return	One Factor Alpha	Three Factor Alpha	Four Factor Alpha
CUSS1	0.02 (0.10)	-0.04 (-0.24)	0.02 (0.15)	0.10 (0.63)	*SUPS1*	0.31 (1.24)	-0.01 (-0.01)	-0.02 (-0.10)	0.08 (0.35)
CUSS2	-0.06 (-0.41)	-0.07 (-0.43)	-0.03 (-0.20)	0.01 (0.07)	*SUPS2*	-0.07 (-0.31)	-0.28 (-1.20)	-0.33 (-1.48)	-0.13 (-0.60)
CUSS3	0.11 (0.57)	0.08 (0.40)	0.26 (1.28)	0.30 (1.55)	*SUPS3*	-0.27 (-1.12)	-0.51** (-2.17)	-0.57** (-2.54)	-0.45** (-1.98)
CUSS4	-0.17 (-0.88)	-0.21 (-1.11)	-0.06 (-0.34)	-0.06 (-0.33)	*SUPS4*	-0.02 (-0.09)	-0.24 (-1.09)	-0.32 (-1.48)	-0.19 (-0.86)
CUSS5	-0.38* (-1.73)	-0.44* (-1.96)	-0.35* (-1.67)	-0.20 (-1.20)	*SUPS5*	-0.09 (-0.33)	-0.40 (-1.55)	-0.40 (-1.61)	-0.23 (-0.93)

Panel E. Average monthly number of links in each portfolio

	SUPS1	*SUPS2*	*SUPS3*	*SUPS4*	*SUPS5*
CUSS1	1097	1114	1114	1114	1099
CUSS 2	1101	1114	1121	1116	1105
CUSS 3	1099	1124	1116	1115	1103
CUSS4	1091	1129	1118	1118	1103
CUSS5	1093	1122	1113	1112	1102

Table 2.6. Regression analysis - Short Interest and Customer's One Month Future Return

This table presents the results from regressions in which the dependent variables are customer's future one month return and the independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. The dependent variables are raw stock returns and one month is skipped between measurement of the independent and dependent variables. I apply log transformations to SIZE and BM. All variables are winsorized at 1% .All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Supplier Short	-0.034***	-0.032***		-0.027***	-0.031***	-0.036**
	(-5.31)	(-5.23)		(-4.45)	(-5.02)	(-5.28)
Customer Short	-0.061***	-0.043**	-0.049**	-0.055**		
	(-2.69)	(-1.99)	(-2.37)	(-2.44)		
Customer Size		-0.022	-0.032	-0.023	0.005	
		(-0.93)	(-1.37)	(-0.97)	(0.24)	
Customer BM		0.281***	0.292***	0.291***	0.292***	
		(3.38)	(3.85)	(3.92)	(3.95)	
Customer IO		0.067	0.018	0.120	0.036	
		(0.52)	(0.14)	(0.86)	(0.26)	
Customer MOM		0.011***	0.011***	0.011***	0.011***	
		(5.91)	(5.95)	(5.93)	(5.85)	
Supplier Size				-0.046***	-0.047***	-0.042**
				(-3.02)	(-3.08)	(-2.75)
Supplier BM				0.033	0.028	0.077*
				(0.94)	(0.81)	(1.89)
Supplier IO				0.061	0.029	0.054
				(0.66)	(0.32)	(0.62)
Supplier MOM				-0.000	-0.000	0.000*
				(-1.18)	(-1.04)	(1.89)
Intercept	1.152***	1.492***	1.559***	1.721***	1.415***	1.267**
	(22.65)	(7.33)	(7.71)	(8.41)	(7.39)	(17.52)
R-squared	0.054%	0.239%	0.221%	0.249%	0.229%	0.041%

Table 2.7. Regression analysis - Short Interest and Customer's 12 Month Future Return

This table presents the results from regressions in which the dependent variables are customer's returns. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. The dependent variables are raw stock returns and one month is skipped between measurement of the independent and dependent variables. I apply log transformations to SIZE and BM. All variables are winsorized at 1% .All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Supplier Short	-0.510***	-0.362***		-0.327***	-0.327***	-0.347**
	(-5.31)	(-4.63)		(-4.52)	(-4.84)	(-4.95)
Customer Short	0.417	0.253	0.174	0.078		
	(1.43)	(0.69)	(0.48)	(0.22)		
Customer Size		-1.761***	-1.874***	-1.806***	-1.822***	
		(-5.61)	(-5.99)	(-5.55)	(-5.73)	
Customer BM		2.928**	2.947**	2.873**	2.873**	
		(2.53)	(2.50)	(2.55)	(2.57)	
Customer IO		-4.689**	-5.289***	-4.037**	-3.861**	
		(-2.47)	(-2.77)	(-2.06)	(-2.01)	
Customer MOM		0.015	0.017	0.019	0.019	
		(0.55)	(0.63)	(0.75)	(0.73)	
Supplier Size				-0.460**	-0.460***	-0.649***
				(-2.58)	(-2.60)	(-3.76)
Supplier BM				0.047	0.036	0.602
				(0.10)	(0.08)	(1.12)
Supplier IO				1.116	1.183	-0.209
				(1.04)	(1.07)	(-0.22)
Supplier MOM				-0.019***	-0.019***	-0.021***
				(-3.57)	(-3.52)	(-4.48)
Intercept	14.839***	36.355***	36.910***	38.823***	39.002***	19.388**
	(24.65)	(12.02)	(12.26)	(12.41)	(12.96)	(19.60)
R-squared	0.214%	1.390%	1.298%	1.507%	1.500%	0.398%

Table 2.8. Regression analysis - Short Interest and Supplier's One Month Future Return

This table presents the results from regressions in which the dependent variables are supplier's returns. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. The dependent variables are raw stock returns and one month is skipped between measurement of the independent and dependent variables. I apply log transformations to SIZE and BM. All variables are winsorized at 1% .All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Customer Short	0.008	-0.008		0.007	-0.005	0.004
	(0.65)	(-0.66)		(0.48)	(-0.36)	(0.33)
Supplier Short	-0.099***	-0.085***	-0.087**	-0.087**		
	(-9.55)	(-7.07)	(-4.30)	(-7.11)		
Supplier Size		-0.096***	-0.097***	-0.099***	-0.125***	
		(-4.25)	(-4.30)	(-4.13)	(-5.03)	
Supplier BM		0.687***	0.682***	0.635***	0.685***	
		(10.68)	(10.55)	(9.46)	(10.24)	
Supplier IO		0.866***	0.881***	0.819***	0.522***	
		(5.84)	(5.96)	(5.29)	(3.74)	
Supplier MOM		0.005***	0.005***	0.004***	0.004***	
		(6.96)	(6.54)	(4.76)	(4.91)	
Customer Size				0.019	0.007	0.028
				(0.92)	(0.34)	(1.48)
Customer BM				0.212***	0.216***	0.367***
				(3.60)	(3.65)	(6.55)
Customer IO				0.229**	0.157	0.177*
				(2.14)	(1.48)	(1.76)
Customer MOM				0.008***	0.008***	0.009***
				(7.49)	(7.86)	(8.70)
Intercept	1.177***	1.838***	1.824***	1.629***	1.839***	0.801***
	(25.21)	(16.50)	(16.65)	(8.02)	(9.00)	(4.28)
R-squared	0.051%	0.213%	0.208%	0.242%	0.207%	0.053%

Table 2.9. Regression analysis - Short Interest and Supplier's 12 Month Future Return

This table presents the results from regressions in which the dependent variable is supplier's 12 month cumulative returns. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. The dependent variables are raw stock returns and one month is skipped between measurement of the independent and dependent variables. I apply log transformations to SIZE and BM. All variables are winsorized at 1% .All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Customer Short	0.946*** (4.93)	0.759*** (3.60)		0.752*** (3.10)	0.596** (2.47)	0.612*** (2.75)
Supplier Short	-1.521*** (-12.19)	-0.954*** (-6.24)	-0.901*** (-5.93)	-1.066*** (-6.80)		
Supplier Size		-3.259*** (-7.96)	-3.266*** (-7.97)	-3.435*** (-7.53)	-3.716*** (-7.95)	
Supplier BM		5.148*** (5.86)	5.160*** (5.87)	5.002*** (5.62)	5.707*** (6.53)	
Supplier IO		4.947** (2.23)	5.456** (2.46)	5.441** (2.31)	1.532 (0.70)	
Supplier MOM		-0.051*** (-5.39)	-0.052*** (-5.52)	-0.046*** (-4.58)	-0.044*** (-4.36)	
Customer Size				-0.048 (-0.14)	-0.188 (-0.57)	-0.619** (-2.22)
Customer BM				-0.703 (-0.71)	-0.661 (-0.66)	0.175 (0.19)
Customer IO				3.784** (2.06)	2.944 (1.61)	0.068 (0.04)
Customer MOM				-0.029* (-1.90)	-0.024 (-1.59)	-0.054*** (-3.62)
Intercept	19.705*** (27.07)	38.462*** (17.50)	39.708*** (18.00)	37.805*** (11.36)	40.386*** (12.24)	23.424*** (8.77)
R-squared	0.461%	1.515%	1.471%	1.588%	1.416%	0.111%

Table 2.10. Average portfolio earnings surprise

This table presents average returns (in %) for portfolios sorted on monthly short interest, SUPS, and monthly short interest for the customer, CUSS. Monthly short interest data in Panel A. is defined as the percentage of total shares shorted divided by the total shares outstanding measured at the midst of each month. The sample consists of common stocks listed on NASDAQ and NYSE from June 1988 through December 2015. The portfolios are rebalanced every month and we skip a month between portfolio formation and the holding period. Panel A shows the results for average standardized earnings surprise of suppliers and Panel B shows the results for average standardized earnings surprise of customers. The table also presents the average returns of the high-minus-low short interest, within each short interest group. All sorts are independently conducted. ***, **, and * denote statistical significance level at the 1%, 5%, 10% levels, respectively.

Panel A. Average portfolio SUE for Supplier

	SUPS1	*SUPS2*	*SUPS3*	*SUPS4*	*SUPS5*	*SUPS5- SUPS1*	*t*
CUSS1	-0.05	-0.07	-0.01	0.03	-0.20	-0.15	-1.24
CUSS 2	-0.08	-0.07	-0.15	-0.14	-0.13	-0.05	-0.38
CUSS 3	0.06	-0.05	0.01	-0.04	-0.10	-0.17*	-1.78
CUSS4	0.08	-0.05	0.03	-0.06	-0.18	-0.26**	-2.36
CUSS5	0.08	-0.18	-0.11	-0.14	-0.24	-0.32**	-2.57
CUSS5 – CUSS1	0.13	-0.11	-0.10	-0.17	-0.04		
t	1.09	-0.82	-1.00	-1.46	-0.43		

Panel B. Average portfolio SUE for customers

	SUPS1	*SUPS2*	*SUPS3*	*SUPS4*	*SUPS5*	*SUPS5- SUPS1*	*t*
CUSS1	0.03	0.06	-0.02	-0.08	-0.02	-0.04	-0.66
CUSS 2	0.00	-0.01	0.00	-0.05	-0.06	-0.06	-1.15
CUSS 3	0.07	0.03	-0.01	-0.10	-0.01	-0.08	-1.12
CUSS4	0.02	0.19	0.23	0.17	0.06	0.05	0.55
CUSS5	0.14	0.04	0.18	0.07	-0.01	-0.15*	-1.78
CUSS5 – CUSS1	0.11	-0.02	0.20**	0.14	0.01		
t	1.28	-0.19	1.91	1.36	0.10		

Table 2.11. Regression analysis - Short Interest and Customer's Future Earnings Surprise

This table presents the results from regressions in which the dependent variable is customer's next quarter earnings surprise. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. I apply log transformations to SIZE. All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Supplier Short	-0.001	-0.002*		-0.003**	-0.003***	-0.003*
	(-0.19)	(-1.87)		(-2.53)	(-2.74)	(-1.93)
Customer Short	-0.003	-0.001	-0.001	-0.001		
	(-0.56)	(-0.24)	(-0.46)	(-0.40)		
Customer Size		0.011***	0.010***	0.010***	0.010***	
		(3.87)	(3.58)	(3.51)	(3.55)	
Customer BM		-0.004	-0.004	-0.004	-0.004	
		(-0.62)	(-0.63)	(-0.57)	(-0.58)	
Customer IO		0.017	0.025	0.023	0.021	
		(1.26)	(1.09)	(1.00)	(1.03)	
Customer Lag SUE		0.396***	0.396***	0.393***	0.393***	
		(17.86)	(17.76)	(17.88)	(17.93)	
Supplier Size				0.008**	0.008**	0.013**
				(2.39)	(2.39)	(2.62)
Supplier BM				0.000	0.000	-0.000
				(0.30)	(0.28)	(-0.71)
Supplier IO				-0.004	-0.004	-0.004
				(-0.31)	(-0.41)	(0.67)
Supplier Lag SUE				0.015***	0.015***	0.013***
				(8.55)	(8.69)	(9.02)
Intercept	0.053***	-0.079***	-0.074**	-0.101***	-0.106***	-0.016***
	(4.70)	(-2.67)	(-2.50)	(-3.14)	(-3.14)	(-0.81)
R-squared	0.007%	15.720%	15.690%	15.940%	15.940%	6.249%

Table 2.12. Regression analysis - Short Interest and Supplier's Future Earnings Surprise

This table presents the results from regressions in which the dependent variable is supplier's next quarter earnings surprise. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. I apply log transformations to SIZE. All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Customer Short	-0.009**	-0.007**		-0.008**	-0.010***	-0.014*
	(-2.03)	(-2.11)		(-2.29)	(-2.74)	(-2.67)
Supplier Short	-0.009***	-0.011***	-0.011***	-0.012***		
	(-2.77)	(-3.89)	(-4.07)	(-4.20)		
Supplier Size		0.023***	0.023***	0.023***	0.015***	
		(3.82)	(3.88)	(3.33)	(2.68)	
Supplier BM		-0.004*	-0.004*	-0.004*	-0.004*	
		(-1.74)	(-1.73)	(-1.75)	(-1.75)	
Supplier IO		-0.040	-0.040	-0.040	-0.101***	
		(-1.14)	(-1.26)	(-1.59)	(-2.98)	
Supplier Lag SUE		0.352***	0.352***	0.352***	0.349***	
		(48.50)	(48.55)	(47.50)	(48.50)	
Customer Size				0.004	0.003	0.004
				(0.95)	(0.70)	(0.57)
Customer BM				-0.007*	-0.007	-0.011**
				(-1.76)	(-1.63)	(-2.52)
Customer IO				0.113***	0.101***	0.134***
				(4.13)	(3.71)	(3.58)
Customer Lag SUE				0.094***	0.094***	0.176***
				(9.13)	(9.09)	(13.96)
Intercept	-0.011	-0.103***	-0.118***	-0.175***	-0.150***	-0.131*
	(-0.63)	(-3.18)	(-3.56)	(-3.14)	(-2.69)	(-1.86)
R-squared	0.004%	12.330%	12.330%	12.550%	12.550%	6.120%

Table 2.13. Customer's Short sale constraint

This table presents the results from regressions in which the dependent variable is customer's next quarter earnings surprise. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. I apply log transformations to SIZE. All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

Dependent variable " Customer Earnings Surprise		
	Model 1	Model 2
Supplier Short	-0.001	-0.001
	(-1.13)	(-0.25)
Customer Short	0.002	0.001
	(0.51)	(0.58)
Customer Size	0.010***	0.010***
	(3.51)	(3.71)
Customer BM	-0.004	-0.004
	(-0.57)	(-0.62)
Customer IO	0.021	0.023
	(1.05)	(1.11)
Customer Lag surprise	0.393***	0.393***
	(17.89)	(17.92)
Supplier Size	0.008**	
	(2.36)	
Supplier BM	0.000	
	(0.30)	
Supplier IO	-0.006	
	(-0.29)	
Supplier Lag surprise	0.015***	
	(8.56)	
Supplier Short Customer High Short*	-0.0012**	-0.0012**
	(-2.13)	(-2.18)
Intercept	-0.102***	-0.082***
	(-3.17)	(-2.76)
R-squared	15.97%	15.75%

Table 2.14. Supplier's Short sale constraint

This table presents the results from regressions in which the dependent variable is supplier's next quarter earnings surprise. The independent variables are various stock characteristics. The sample consists of common stocks listed on NASDAQ and NYSE from 1988 through 2015. I apply log transformations to SIZE. All regressions are clustered by firm. T-statistics are reported below the coefficient estimates. ***, **, and * denote statistical significance level at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Supplier Earnings Surprise		
	Model 1	Model 2
Customer Short	-0.005	-0.004
	(-1.27)	(-0.89)
Supplier Short	-0.008**	-0.007**
	(-2.55)	(-2.13)
Supplier Size	0.019***	0.021***
	(3.30)	(3.67)
Supplier BM	-0.004*	-0.004*
	(-1.74)	(-1.74)
Supplier IO	-0.061*	-0.045
	(-1.69)	(-1.27)
Supplier lag Surprise	0.348***	0.351***
	(43.81)	(43.48)
Customer Size	0.004	
	(0.86)	
Customer BM	-0.007*	
	(-1.74)	
Customer IO	0.112***	
	(4.08)	
Customer lag Surprise	0.094***	
	(9.13)	
Customer Short Supplier High Short*	-0.024**	-0.026**
	(-2.47)	(-2.76)
Intercept	-0.175***	-0.109***
	(-3.14)	(-3.33)
R-squared	12.56%	12.35%

Appendix.

Table 2.15. Average portfolio returns (two month lagged short interest)

This table presents average returns (in %) for portfolios sorted on monthly short interest, S, and monthly short interest for the customer, CS. S and CS are relative monthly short interest and are defined as total shares shorted divided by the total shares outstanding measured mid-month. The sample consists of common stocks listed on NASDAQ and NYSE from June 1980 through December 2015. The portfolios are rebalanced every month and we skip a month between portfolio formation and the holding period. Panel A shows the results for average returns of suppliers and Panel B shows the results for average returns of customers. The table also presents the average returns of the high-minus-low short interest, within each short interest group. All sorts are independently conducted. ***, **, and * denote statistical significance level at the 1%, 5%, 10% levels, respectively.

Panel A. Supplier's average return

	SUPS1	SUPS2	SUPS3	SUPS4	SUPS5	SUPS5- SUPS1	t
CUSS1	1.37	1.09	1.14	0.8	0.40	-0.97***	-3.04
CUSS 2	1.10	1.49	0.83	1.09	0.77	-0.32	-0.95
CUSS 3	1.46	1.14	1.01	1.18	0.36	-1.10***	-3.27
CUSS4	1.15	1.63	1.44	1.08	0.53	-0.62**	-2.00
CUSS5	1.56	1.24	1.30	1.14	0.62	-0.94***	-2.80
CUSS5 – CUSS1	0.18	0.15	0.16	0.34	0.21		
t	0.73	0.60	0.61	1.37	0.72		

Panel B. Customers' average return

	SUPS1	SUPS2	SUPS3	SUPS4	SUPS5	SUPS5- SUPS1	t
CUSS1	0.98	1.07	1.16	0.76	0.82	-0.16	-1.01
CUSS 2	1.16	1.24	1.14	1.22	1.25	0.09	0.61
CUSS 3	1.14	0.99	1.06	1.21	1.20	0.06	0.29
CUSS4	1.21	1.26	1.12	1.13	1.22	0.01	0.07
CUSS5	1.21	0.88	0.87	1.02	0.76	-0.45**	-2.17
CUSS5 – CUSS1	0.23	-0.20	-0.29	0.26	-0.06		
t	1.01	-0.80	-1.18	1.05	-0.21		