TWO ESSAYS ON CUSTOMER-SUPPLIER NETWORK AND TRADE SECRETS

by

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A Dissertation Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

in Management Science

at

The University of Wisconsin-Milwaukee

May 2019

ABSTRACT

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The University of Wisconsin-Milwaukee, 2019
Under the Supervision of Professor Valeriy Sibilkov

This dissertation investigates two important topics: idiosyncratic shock aggregation in customer-supplier network and impacts of trade secret litigations on stock performance. The first essay studies the underlying factors for stock returns comovement between customer and supplier firm. The investigation further explores the idiosyncratic shocks propagation and aggregation in the network. The second essay documents the stock market reactions to trade secret lawsuit outcomes and its economic meanings to the industry.

The first essay, Idiosyncratic Shocks Aggregation in Customer-Supplier Network, is inspired by Acemoglu, et al. (2012)'s theoretical work and Cohen and Frazzini (2008)'s empirical study. Traditional theory regarding idiosyncratic shocks suggest diversification effect averages out microeconomic shocks within each sector of an interconnected network. However, more and more recent study shows that idiosyncratic shocks may translate into aggregate shocks if the interconnected system is asymmetric. Empirical research in customer-supplier network shows that the stock returns of a customer and a supplier firms comove strongly. Idiosyncratic information and earnings news are the key drivers of the stock return comovement induced by the establishment of the customer-supplier relationship. By studying the return connections between customer and supplier firms, I find idiosyncratic shocks propagate and aggregate in this network. A new risk factor formed by aggregating idiosyncratic returns of customer firms is evidently priced in suppliers' returns. This study builds on existing customer-supplier network research and contribute to the literature by pinpointing the information channels

and contents that drive stock return comovement and document a new risk factor in customer-supplier network.

The second essay, Economic Outcomes of Corporate Espionage, uses a unique hand collected trade secret lawsuit dataset, and documents strong stock market reactions to trade secret lawsuit outcomes. Trade secret lawsuit data including file date, plaintiffs and defendants, and court rulings are manually collected from Lexis-Nexis database and carefully screened to determine the directions of court rulings. The empirical results indicate stock market reacts to court outcomes not only at firm level, but also at industry level. Further regression and difference-in-differences analysis suggest strong intellectual properties protection system encourages firms' R&D investment and future growth opportunities.

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Idiosyncratic Shocks Aggregation in Customer-Supplier Network

Abstract

Using customer-supplier networks, we document a strong increase in stock return comovement between customer and supplier after the establishment of their relationship. This increase in comovement is mainly associated with cash flow news and firm-specific information. The idiosyncratic shocks to customers diffuse through the customer-supplier network and aggregate into a systematic risk, which affects suppliers' expected returns. Using a long-short portfolio based on exposure to aggregated customer risk, we realize an annual excess return of 3.1% (value-weighted) and 6.11% (equal-weighted), respectively. The customer risk factor cannot be explained by market, size, book-to-market or momentum factor.

Introduction

On Jan, 3rd 2019, Apple stock tumbled 8.99% in a single day, triggered by a public letter released from Cupertino, California warning lower revenue guidance for the first quarter of 2019. On the same day, the S&P 500 index dropped 1.52%, and Nasdaq closed 1.86% lower. Although Apple was the second largest corporation by market valuation, it did not seem to justify the vast evaporation of the total US market value because the amount disappeared is similar to the total market capitalization of Apple. But if we consider the large number of companies connected to Apple, the impact on Apple can be amplified through its connected economic networks and the shocks to its suppliers accumulate in massive market fluctuations. As in this anecdotal case, it is possible that market-wide shock could originate from an individual company if it is linked to many firms through economic networks.

A large strand of literature in asset pricing have attempted to understand how individual shocks aggregate into market-wide fluctuation. Granular network theory offers a micro-foundation: the aggregation of individual risk becomes a risk at the market-level. Gabaix (2011) and Acemoglu et al. (2012) provide theoretical frameworks that idiosyncratic shocks will aggregate into systematic shocks in the granular network. More evidence is accumulated in recent empirical studies. Kelly, Lustig, and Nieuwerburgh (2013) show that consistent to granular network theory, firm size distribution is a key determinant of firm-level volatility and volatility comovement in the network. Ahern (2013) explores the industry network and finds that industries placed more central in the network exhibit higher risks and returns. These papers only show less direct implications which would hold at the equilibrium level.

In this paper, we fill this gap by studying the propagation of firm-specific shocks through customer-supplier networks and how firm-specific shocks become a systematic risk. Motivated by both theoretical groundwork and the availability of data, we comprehensively investigate the channels of idiosyncratic shocks propagation and the pricing of these shocks in customer-supplier links. Specifically, when firms are connected to other firms along the supply chain, stock returns of these linked firms become more comoving. As a customer is more connected, the shocks to these customers are propagated throughout the connections. The aggregation of idiosyncratic shocks to these customers is a systematic risk factor which does not overlap with existing risk factors. Thus, suppliers with greater exposure to this customer risk factor have higher stock returns.

The customer-supplier relationship is an integral part of companies. For customer firms, supply chain management is an important part of operations and critical to the success of the company. In accordance with their importance, not only does the information pass through this channel, but also the shocks spread to the connected companies. We use the customer-supplier relationship of individual firms as the backbone of granular networks. As a filing requirement, suppliers must declare their principal customers who account for more than 10% of their total sales. We identify these customers for each supplier and construct the complete network using each identified customer-supplier pair. Our sample records a sizable turnover in customer-supplier relationships. Over the thirty-five years sample period, we document over 18,000 customer-supplier pairs consists of 6,492 suppliers and 2,902 customers. More than half of the relationships last for less than two years. The average duration of links is 6.3 years.

We first examine the stock return comovement between customer and supplier firms. Customer-supplier link (hereafter, CSL) return comovement has been documented in several studies (Cohen and Frazzini, 2008 and Cen, Hertzel, and Schiller, 2017). Contrast to the lead-lag comovement recorded in the previous studies, we document strong contemporaneous return comovement between customers and suppliers using our up-to-date CSL sample. We show that the return comovement between two firms increases significantly since the establishment of CSL.

To confirm that the baseline results are not biased, we match each supplier firm (customer firm) with a pseudo-customer (supplier) within the same industry and the same size quintile. The randomly matched pairs have no economic links to each other. However, we still detect a significant degree of return comovement between these pseudo pairs because a substantial amount of CSLs is formed in the same industry, or between related industries. The customer and supplier firms exhibit strong stock prices correlation due to the similarity in their core business and the business cycle. The essential difference is that the return comovement of pseudo pairs does not increase at all during the pseudo linked period, suggesting that increases in return comovement come from the information propagation within the customer-supplier relationship.

We then examine which component of stock returns contributes to increment in return comovement. We decompose customer's returns into cash flow news and discount rate news using a method proposed by Chen, Da, and Zhao (2013, CDZ hereafter). Using decomposed quarterly return data,[1] we find that cash flow news mainly contributes to the increase in comovement, not the discount rate news, especially between the firms who have maintained a long-term relationship. When changing customers' cash flow expectations, investors revise the cash flow expectations of linked suppliers.

We corroborate the comovement in cash flow expectation by examining comovement in earnings surprises, as earnings surprise contains information about the cash flow of the company.

[1] Although conservative, quarter return decomposition is much more reliable and trustworthy than monthly return decomposition because analyst earnings forecasts are disclosed on a quarterly basis.

Forecasting errors obtained from seasonal random-walk models and cumulative post-announcement abnormal returns are used as measures of earnings surprises. We find that the comovement in earnings surprises only exists when CSL is formed, which confirms the vital role of the cash flow channel in a customer-supplier relationship. The comoving earnings surprises suggest that the cash flow channel transmits not only market information, but also firm-specific operating uncertainty because firm-specific information is embedded in earnings news.

According to the literature on return comovement, there could be two possible causes of return comovement. First, comovement results from the alignment of firms' fundamentals. For instance, a customer or supplier firm may be forced to share its profits with its business partner if the partner firm possesses bargaining power. The findings of the synchronous revision in the cash flow expectations for customers and suppliers support this argument. Second, return comovement can be driven by investors' behaviors (Barberis, Shleifer, and Wurgler, 2005; Pirinsky and Wang, 2006). Investors of these stocks can follow similar investment patterns and moves the price of these stocks in the same direction.

A detailed investigation of customer and supplier firms' fundamentals comovement and the underlying determinants of their return comovement is necessary for us to understand the nature of the phenomenon. We find that profitability measures such as profit margin and return on assets comove alongside the return comovement. It confirms that return comovement comes from aligning firms' fundamentals. Next, we examine the determinants of return comovements. Sales concentration is a major driver for return comovement. A supplier with more concentration shows a greater return comovement for the customer. We also find that comovement becomes stronger if the customer's size is larger. Trade credits, link duration, and common institutional ownership all leads to the greater comovements.[2]

Next, we raise the question whether the increment in comovement comes from the increased correlation of firm-specific risk or increased exposure on systematic risk factors. The evidence so far indicates that an increase in return comovement for a customer-supplier relationship is due to idiosyncratic information. Firm-specific risks are predominantly transmitted to connected companies, but a change in systematic risk exposure can be followed when the link is established. For example, suppliers can increase relation-specific investment, which leads to higher exposure to market beta. Our further investigation employs the Fama-French three-factor model in addition to industry returns and decomposes customer and supplier firms' monthly returns into idiosyncratic and systematic components. The result shows that most of the changes in return comovement are caused by firm-specific risk propagation.

From granular network theory, the idiosyncratic risks of individual firms will aggregate into the systematic risk in an asymmetric network. On the other hand, from the canonical risk factor models, idiosyncratic risks should be diversified away and do not have a risk premium. We empirically examine whether aggregated firm-specific risks are priced. Particularly, we aggregate idiosyncratic shocks to customers which have many suppliers. These customers are located more central in the granular network and their firm-specific shocks are more easily propagated and impact other companies, and thus become systematic. We first estimate the

[2] Interestingly, we find the difference in bargaining power between customer and supplier firms reduces the comovement, supported by the effect of ROE and leverage on comovements. Higher ROE of customers or suppliers would imply that they have more bargaining power and do not share their profits with opposite party. Higher leverage is a well-known proxy for bargaining power. If the firms do not share their profits with connected firms, their fundamentals would less comove, resulting in lower return comovement.

supplier firms' exposure to aggregate customer risks. It shows that supplier's exposure to customer risk is directly related to the complexity of its connections to customers. The more customers a supplier has, the higher its risk exposure, which proves that idiosyncratic shocks do aggregate through the network.

To analyze the risk-return relationship of customer risks, we adopt Fama-Macbeth regressions and show that the risk premium of aggregate customer risk is significantly positive. Suppliers' returns increase monotonically with the beta of aggregate customers' idiosyncratic returns. Put it differently, suppliers with greater exposure to aggregate customer risks are perceived as riskier and their stock returns are higher. In turn, we show that firm-specific risks of customers with many suppliers become systematic risks and have a positive risk premium. As a falsification test, we aggregate the idiosyncratic return of customers with less than three suppliers, which is less likely to become systematic in the granular network. Consistently, the risk premium of the pseudo-risk factor does not exist.

We construct the long-short portfolio of suppliers sorted by quintiles on the basis of customer betas. We rebalance the portfolio monthly by buying the supplier stock with the highest customer betas and shorting the supplier firms with the lowest customer betas. The portfolio generates annual excess returns of 3.1% (value-weighted) and 6.11% (equal-weighted), respectively, suggesting that aggregate customer risk cannot be explained by Fama-French three factors or momentum factor.

The first contribution of this paper is to stock return comovement literature. Existing theories suggest return comovement can be driven either by the alignment in firms fundamentals or by investors' behaviors. Recent evidence is more favorable to the latter explanation. For example, comovement in commodity prices is best explained by investors' herding behavior

(Pindyck and Rotemberg, 1988). Barberis, Shleifer, and Wurgler (2005) also show that comovement among S&P 500 index firms is driven not by fundamental but by friction or sentiment.[3] Our paper links comovement to information channel and risk propagation in a business network. Return comovement between linked firms appears to be the result of the fundamental adjustment of both firms.

This paper also contributes to the traditional portfolio theory. Idiosyncratic shocks through an economic network aggregate into systematic shocks. Consistent with Ahern (2013), in a business network, the centrality of the firm is directly linked to its exposure to aggregate risk. The excess returns generated by the long-short portfolio in this paper show that investors view centrality as greater exposure to systematic risk.

Our paper is most closely related to the literature studying the customer-supplier return comovement. Cohen and Frazzini (2008) construct a customer momentum investment strategy designed to exploit investors' inattention to this subtle yet valuable information network. Although the excess returns from such a strategy have diminished in the past decade in a general way, they still exist among customer-supplier relationships where information diffuses slowly (Cen, Hertzel, and Schiller, 2017), or if information of the companies is costly to obtain (Veldkamp, 2006). With an extended CSL dataset and solid theoretical supports, we dissect and analyze the customer-supplier linkage more in-depth and reveal the specific shock propagation, the channels it is passing through, and eventually the pricing of aggregated idiosyncratic shock.

The rest of the paper is organized as follows. Section II describes the data and tablets the summary statistics. Section III presents the baseline results. Section IV investigates the

[3] Stocks with similar price levels also comove due to category restriction (Green and Hwang, 2009). Local investors' investment pattern (Pirinsky and Wang, 2006), analyst coverage (Hameed, Morck, Shen, and Yeung, 2015; Guan, Wong, and Zhang, 2015), and joint institutional ownership (Anton and Polk, 2014) each play a critical role in return comovement.

information flow through the cash flow channel. Section V delves into the fundamental drivers of return comovement. Section VI prices customer firm's idiosyncratic return. Section VII concludes the paper.

Data

Firm's disclosure about segments of an enterprise and related information, also known as FASB statement No. 131, requires the company to report customers accounting for more than 10% of its total annual sales. We extract customer segments data from Compustat, and our customer-supplier link (CSL) dataset covers the period from 1980 to 2015.[4] Some customer names are either presented as abbreviations of the company names or artificially ambiguous due to reporting firms' convenient record keeping. We use computer programs to generate a series of potential matched customers for each equivocal customer name. We then manually identify the real match by cross-referencing using various sources including but not limited to CRSP/Compustat database, company's official website, Bloomberg company files, and Hoover's. We are purposely stringent on the matches, and we only keep those without any ambiguity. Our analysis focuses on the common stocks on NYSE, Nasdaq, and AMEX. We drop firms with stock prices lower than $5 to avoid the impact from the microstructure. Utility firms and financial institutions are also excluded. For each firm in our final sample, we retrieve its return data from CRSP and firm characteristics from the Compustat database.

Table I summarize the CSL data set. The full sample contains 18,088 unique customer-supplier links, across the 35 years. The number of suppliers is more than the double of the number of customers, which is expected given the average size of customers is ten times as large as that of suppliers. Customer firms are also more connected than supplier firms. Customer firms

[4] We expand the CSL samples of Cohen and Frazzini (2008) by extending sample period to 2015 and matching customers more accurately.

have an average of 6.2 suppliers, comparing to only 2.6 customers per supplier. The most connected customer firm in our sample is Walmart. The company has reported a total of 450 suppliers over a span of 35 years. The most connected supplier, Highwoods Properties Inc., on the other hand, has only reported 36 customers in the same period. In 2976 pairs, linked firms (customer and supplier) come from the same industry. We use Fama-French 48 industries classifications.

Link duration is among the key variables in our primary analysis. Mean duration is 6.3 years, and the most enduring link is almost as extensive as the whole sample period. One fact to note is that the distribution of the link durations is right-skewed. More than 50% of the links (9873 to be exact) last for less than two years, while the long-term links (duration longer than five years) account for more than 25% of the full sample. Our empirical evidence in the main analysis supports the prediction that a long-term supplier-customer relationship affects a firm's characteristics and operations more substantially and persistently than a short-term one.

Our baseline comovement tests use weekly returns ending on Wednesdays. We believe that weekly returns are more suitable for our study than daily or monthly returns for two reasons: first, it avoids nonsynchronous trading consequences associated with daily stock returns; second, weekly returns offer more observations comparing to monthly returns. It is critical in our panel regression because more than half of our final sample consists of customer-supplier links that last for less than two years and thus have short time-series. It is imperative to preserve as many observations as possible before and after the CSL announcement to maintain a balanced panel dataset.

One of the primary interests of this paper is to reveal the information channels that connect customer and supplier firms. In general, financial information channels can be classified into two categories: cash flow news and discount rate news. We use implied cost of capital (ICC) approach proposed by Chen, Da, and Zhao (2013, CDZ hereafter) to decompose the returns. Extreme values are inevitable by-product of CDZ's return decomposition methodology because they use direct cash flow forecasts by analysts which contain substatial noise. We winsorize cash flow news and discount rate news to 5 and 95 percentiles to minimize the side effect. In table I, we see that the distribution of discount rate news is much more dispersed than that of cash flow news. It is not surprising since the cash flow news in CDZ's decomposition is simply the analysts' earnings forecast and discount rate news has to absorb all other information.

The cross-sectional statistics of our customer-supplier link sample (panel C of table I) allow us to evaluate the complexity of the network. The majority of the firms report only 1 or 2 customers every year. It is expected because firms are only required to report their principal customers. More than 50% of the customer-supplier links last no more than two years in the sample based on the firm's report. Long-term links, which last longer than five years by our definition, account for a little over 10% of the full sample. Although this does not seem like much, the long-term links are the mainstay of our study because the comovement investigation requires a substantial length in the time-series dimension.

Customer-Supplier Comovement and the Information Channels

Our core analysis estimates the following regression:

$$SRET_{i,t} = \alpha + \beta^{c} CRET_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * CRET_{i,t} + \beta^{MKT} MKT_{i,t} + \beta^{IND} IND_{i,t} + \epsilon_{i,t} \quad (1)$$

SRET is a supplier firm's stock return over the estimation period. CRET is a corresponding customer's stock returns. Link is a dummy variable which takes the value of 1 if two firms have been reported as customer and supplier at the time of observation (linked period), and 0 otherwise (unlinked period). MKT is value-weighted market returns, and IND is the supplier's corresponding industry's value-weighted returns. Both indices exclude corresponding supplier firms. We follow Fama and French (1992) industry classification to form 48 industry portfolios. We select value-weighted market and industry indices in response to the massive firm size differences between supplier and customer firms. In an unreported robustness check, we replace the value-weighted index with equal-weighted ones. All the results stay highly consistent, and all the references remain unchanged.

We analyze information channel directly using customer-supplier pairs instead of aggregating suppliers' news for a customer or customers' news for a supplier because more than 50% of the customer-supplier links are short-lived. If we form a customer portfolio for a supplier firm, the underlying companies within the portfolio change drastically from one report date to the next, resulting in disorganized and unbalanced customer portfolio. Also, constructing a customer portfolio is useless for a large number of suppliers with only one customer. Moreover, customer portfolio formation artificially creates observation gaps[5].

Table II presents the baseline results of this paper. The return regressions use weekly returns. In our robustness check, We use monthly returns to rerun all the return comovement tests. All results stay highly consistent, and no changes in the inferences are spotted. Link duration varies across the final sample links. To both fit our regression model with a balanced panel dataset, we analyze the comovement using subsets with different link durations. The different duration subsets allow us to examine the impact of link duration on the comovements. We test the return comovement in three subsets: CSLs with minimum link duration of two, three,

[5] E.g., firm A reported one customer, firm B, in 1980, and another customer, firm C, in 1985. Our study considered them as two independent links. However, firm A's customer portfolio, in this case, doesn't offer economic meanings, nor helps reveal the information channels.

and five years.[6] We maintain a balanced panel dataset for all three subsets. For example, the unlinked period for the five-year subset is (t-84, t-24) months and the linked period is (t, t+60) months from the cutoff point. The cutoff point is the earliest date when a CSL is reported. The two-year gap in between unlinked and linked period is to address the concern that a customer-supplier relationship exists before it is acknowledged by the public because companies are only required to report their principal customers who contribute to at least 10% of their sales.

The return comovement factors of customer-supplier relationship can be classified into three categories. First, market (systematic) influences such as GDP growth, inflation, employment rate, and economic healthiness affect all stocks. Although these factors move stock prices in a general way, their impact is lower than those of industries. The second category, industry impact, accommodates much richer information including but not limited to the proximity of operations and core business among firms, industrial growth opportunities, intra-industry information flow and networking, and industry oriented institutional investing. The final category is customer-supplier link specific information, which is also the primary interest of this paper, consists of the closeness of a link, link duration, common institutional ownership, and firm characteristics.

The empirical evidence supports our claims. Panel A of Table II shows the industry's influence on stock returns is not only eight times as large as the market's, but much more significant. It is critical for us to control both market and industry interference to highlight the designated information channels that transmit news along the supply chain.

Even after controlling for market and industry returns, we still cannot claim the comovement between customer and supplier firms is directly driven by such a relationship. We

[6] The subsets are not mutually exclusive. The subset with three-year link duration are always a part of subset with two-year link duration.

want to discover the information channels specifically associated with the customer-supplier relationship. Customer and supplier firms' returns may covary before their relationship begins due to the proximity in their core business and main operations. Only the differences in comovement between the linked and unlinked period give us the insight of channels that host link-specific information. Information never stops flowing between firms, especially if two companies are within the same industry. Twenty-five percent of our customer-supplier pairs come from the same industry, and more come from related industries. Market and industry influences are unlikely to change suddenly due to an announcement of the customer-supplier link because such a message is firm-specific information, not systematic. If additional comovement is detected following the disclosure, it is mainly related to this economic link. And the associated information channel is exclusive to the customer-supplier relationship.

Our panel regression model is very similar to those used in the difference-in-differences analysis. The core difference is that we only have one dummy variable. We are interested in the comovement purely induced by customer-supplier link information and the information channel through which this information passes.

The baseline results reveal that return comovement between supplier and customer firms are highly significant across the sample. For every 1% increase in customer firm's return, the supplier's return increases about 0.08% even when they are not linked. After the public has acknowledged the relationship, the comovement increases by approximately 20%. Apparently, there is an information channel connecting supplier and customer firms. Panel A shows that a substantial portion of the return comovement between supplier and customer firms in our sample is driven by various market and industry factors, and some unobservable factors. The comovement exists prior to the customer-supplier relationship, but the link increases comovement to a significantly higher level.

Undeniably, there is more than one way to categorize information channels. However, the building block of financial valuation models relies on two elements: cash flow and discount rate. Recent studies have been debating the importance of cash flow news relative to discount rate news in stock prices movement (Goyal and Welch 2008; Larrain and Yogo 2008; Chen, Da, and Priestley 2012). Coincidentally, researchers are discussing the effects of investor's behavior comparing to firms' fundamentals when explaining return comovement.

Building upon the intuitions and insights of existing literature, the total comovement between supplier and customer should be driven by both cash flow and discount rate news. However, it is unclear what is driving the increase in comovement induced by the establishment of the customer-supplier link. Cohen and Frazzini (2008) show customer portfolio's return can predict corresponding supplier's return for up to a month because of investor's inattention to this important economic links. Nonetheless, investor's attention is supposed to eliminate the information lag, instead of driving the comovement increase. A more plausible explanation is that the boost in the comovement is driven by the cash flow news of customer and supplier firms. No rational investment patterns, nor diversification needs will urge investors to buy or sell both customer and supplier firms simultaneously.

To further investigate, we use a return decomposition approach proposed by Chen, Da, and Zhao (CDZ) (2013) and decompose customer's returns into cash flow news and discount rates news. The approach extracts prevailing analyst earnings forecasts from IBES as direct measures of a firm's expected future cash flows, to back out the implied cost of capital (ICC). The CDZ return decomposition singles out the cash flow news and allow us to explicitly examine the relationship between firms' fundamentals and the increase in CSL return comovement. In panel B and C of Table II, we test the comovement between the supplier's returns and these two components of the customer's return:

$$SRET_{i,t} = \alpha + \beta^{c} C\_CF_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * C\_CF_{i,t} + \beta^{MKT} MKT\_CF_{i,t} + \beta^{IND} IND\_CF_{i,t} + \epsilon_{i,t} \quad (2)$$

$$SRET_{i,t} = \alpha + \beta^{c} C\_DR_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * C\_DR_{i,t} + \beta^{MKT} MKT\_DR_{i,t} + \beta^{IND} IND\_DR_{i,t} + \epsilon_{i,t} \quad (3)$$

C_CF is a customer's cash flow news, and C_DR is a customer's discount rate news. MKT_CF/MKT_DR is the market-wide value weighted cash flow news/discount rate news, and IND_CF/IND_DR is the industry value-weighted cash flow news/discount rate news. We find customer's discount rate news affect supplier's returns across the whole sample. However, we do not detect any change in comovement after two firms become business partners or the link is known to the public. It suggests that the increases in comovement we document in Panel A are not driven by the information related to the discount rate. CSL changes both firms' fundamentals and investor's expectations of the future cash flows. A successful long-term customer-supplier relationship reduces the volatility in supplier's cash flows and the business risk of both sides, resulting in stronger comovement due to the cash flow news, and such a claim is solidly supported by empirical evidence. In this sense, the return comovement through the customer-supplier link is distinguished from the comovement among S&P500 firms (Barberis, Shleifer, and Wurgler, 2005) or geographically close firms (Pirinsky and Wang, 2006).

Panel B and C of Table II definitely point out, for all CSLs that last longer than five years, the increase in comovement from CSL establishment is solely driven by customer's cash flow news. The information channel that connects supplier and customer firms always exists, even before they cooperate. The business partnership leads to additional cash flow news passage between the participating companies. Such cash flow news could contain information about mutual extra earnings or savings in the business operations, or comovement in some other fundamental variables. It takes an abiding partnership to allow this implicit cash flow news to aggregate to a level where it is powerful enough to align stock returns. Our results shed light on the empirical return comovement researches where scholars tend to find the importance of investor's behaviors dominates that of the firm's fundamentals.

The insight of (CDZ, 2013) is that cash flow news is more important than discount rate news if accumulated over a long investment horizon. Discount rate news is rather transitory. Over time, its return driving power will deteriorate and eventually be outweighed by cash flow news, which is fundamentals related. The baseline return decomposition is revised quarterly based on analyst earnings forecasts. Nevertheless, the model can be altered to estimate monthly cash flow news and discount rate news. As a robustness check, we rerun panel B and pane C in Table II using monthly CDZ decomposition. Although the significance of some results decreases, the overall implications of the results are the same.

Previously we claim that market and industry factors drive a significant portion of return comovement between supplier and customer stocks. Also, we state the economic connection after CSL establishment primarily induces the increase in comovement. To validate these propositions, we test the return comovement among pseudo-customer-supplier pairs. For each customer (supplier) firm in the sample, we randomly identify a matched company within the same stock exchange, the same size quintile classified by NYSE common stock breakpoints, and the same industry categorized by Fama-French 48 industry classification. When identifying the matches, we make sure each matched pair has never had a real economic connection.

Table III estimate the following model:

$$SRET_{i,t} = \alpha + \beta^{c}PCRET_{i,t} + \gamma^{link}Link_{i,t} + \beta^{LC}Link * PCRET_{i,t} + \beta^{MKT}MKT_{i,t} + \beta^{IND}IND_{i,t} + \epsilon_{i,t} \qquad (4)$$

$$PSRET_{i,t} = \alpha + \beta^{c} CRET_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * CRET_{i,t} + \beta^{MKT} MKT_{t} + \beta^{IND} IND_{j,t} + \epsilon_{i,t} \qquad (5)$$

PCRET (PSRET) is the return of a pseudo-customer (pseudo-supplier) over the linked and unlinked period. The tests in Table III are identical to those conducted in Table II. In addition to stock returns comovement analysis, we decompose customer and pseudo customer's returns into cash flow news and discount rate news and run the model (2) and (3) for the pseudo pairs we form.

The coefficients of PCRET and CRET in Table III suggest a strong correlation in stock returns between these pseudo pairs even if there are no real business connections. Since the pseudo-customer and pseudo-supplier are selected from the same stock exchange and the same industry, we can safely assume market and industry factors are driving the comovement in these pseudo pairs. More importantly, we do not observe any increase in comovement in any analysis or any subset during the linked period. Cash flow and discount rate component analysis suggest the same inferences.

Comovement and Idiosyncratic Information

The baseline result indicates that cash flow channel is vital to the customer-supplier relationship. However, it remains to consider what information is transmitted through this channel and leads to greater return comovement. Although the a customer-supplier relationship makes the firms to engage in relation-specific investments, which generates more synchronous cash flows between these firms, we cannot rule out the possibility that increased exposure to the systematic risks may induce a greater comovement. To further investigate the channel, we decompose both customer and supplier's returns into idiosyncratic and systematic components.

Table IV tests the comovement of both idiosyncratic and systematic monthly returns of linked firms. Idiosyncratic and systematic returns are estimated using regression model (6).

$$R_{i,t} = \alpha + \beta_{MKT}MKT_{i,t} + \beta_{SMB}SMB_{i,t} + \beta_{HML}HML_{i,t} + \beta_{IND}IND_{i,t} + \varepsilon_{i,t} \quad (6)$$

We use Fama-French three factors and industry returns to decompose the firm's excess returns. Excess returns are calculated by subtracting the U.S. T-bill rates from stock returns. Monthly factors and risk-free rate data are retrieved from WRDS. We also add industry value-weighted return to the regression to control the substantial industry influence on customer-supplier return comovement. We calculate the industry value-weighted return of each firm and the corresponding firm is excluded . We employ 60-month rolling windows, i.e. (t-59, t) months, to estimate the coefficients of the four independent variables. Then we predict the stock return in the month (t+1 month) following estimation window using the estimated coefficients as well as Fama-French three factors (MKT, SMB, HML) and industry value-weighted return in (t+1) month. The predicted return is the systematic component, and the prediction error is the idiosyncratic return. This return decomposition method relies on regression predictability. To make sure the robustness of the results, we also decompose the return using daily returns. We verify the idiosyncratic and systematic return comovement using these daily decomposed return, and all the results remain the same.

The regressions in Table IV resemble the tests in Table II and III. The differences are, in Table IV, the dependent variable is the supplier's idiosyncratic/systematic return. The independent variable CRET represents the customer's idiosyncratic/systematic return. Link is a dummy variable which takes the value of 1 if two firms have been reported as customer and supplier at the time of observation (linked period), and 0 otherwise (unlinked period). MKT is market-wide value-weighted idiosyncratic/systematic return, and IND is industry-wide indices.

Table IV unambiguously indicates that CSL-induced return comovement is determined by the firm-specific information flow between the linked customer-suppler firms. For the CSLs longer than three years, the comovement in idiosyncratic returns becomes double during the linked period. The idiosyncratic return comovement increases almost triple for the subset of CSLs with 8 year link duration. We find strong comovement between supplier and customer's systematic returns, but, the systematic comovement in the linked period does not differ from that in the unliked period.

The results imply that supplier and customer firm's idiosyncratic returns are more correlated after the start of their cooperation. There is no increase in exposure to common systematic risks induced from the formation of the customer-supplier link. The investors are sophisticated enough to incorporate the idiosyncratic information of customers into the stock prices of suppliers of the CSL. The low r-squares in the regression for idiosyncratic return comovement should not be surprising because idiosyncratic shock are orthogonal to systematic ones and technically needs to be orthogonal to idiosyncratic shock of the other company. It is important to note that these idiosyncratic shocks to customers and suppliers may not be from the separate correlated events. The key is that, if there is an unique event to either customer and supplier, the shock of one company is transferred to other company and moves their stock price in the same direction.

The importance of idiosyncratic return for the stock return dynamics draw a lot of researchers' attention since Campbell, Lettau, Malkiel, and Xu (2001) documented the up-trend in firm-level idiosyncratic volatility in the recent decades. Numerous attempts have been made to explain the idiosyncratic volatility puzzle. Some find a negative relationship between expected stock returns and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006 & 2009; Stambaugh, Yu, and Yuan 2015). The others argue that there is no significant relationship between expected stock returns and idiosyncratic volatility (Bali and Cakici, 2008; Guo, Kassa, and Ferguson 2014).[7] These firm-specific returns and volatility is closely related to earnings information (Jiang, Xu, and Yao 2009; Zhang, 2010). Following the existing evidence, earnings surprises would contain more idiosyncratic cash flow news than discount rate news. .

In Table V, we examine comovement between long-term supplier and customer's earnings surprises using four different measures of earnings surprises. The first two measures, RET5 and RET21, are 5 trading day and 21 trading day post-earnings announcement cumlative abnormal returns (CAR). The CARs of supplier and customer are calculated from the customer's earnings announcement date in each reporting quarter if the annoucement dates of the linked firms are different. We also utilize standardized unexpected earnings (SUE1), which is calculated based on a rolling seasonal random walk model (Livnat and Mendenhall, 2006) and standardized unexpected earnings accounting for the exclusion of special items (SUE2). We do not use earnings surprises from analysts' forecasts because they can follow Non-GAAP standards, and carry a different form of mispricing (Livnat and Mendenhall, 2006), which is not desired in this study. The analysts' subjectivities can introduce additional noise to earnings surprises. Our study focuses on the movements in firms' stock returns, along with operations and fundamentals.

Table V shows significant increases in the comovement between customer's and supplier's 5-day CAR (RET5) and 21-day CAR (RET21) across all three subsamples. The increases in return comovement are not surprising given our baseline results, but the magnitude of the increases is noteworthy. The increases in comovement are more prominent during the event periods than normal times. There is no significant correlation between the customer and supplier's 5-day cumulative returns (RET5), when an economic linkhas not been established.

[7] Fu (2009) exceptionally documents a positive relationship between expected stock returns and idiosyncratic volatility.

Although the 21-day cumulative returns (RET21) of customer and supplier comove before the linked period, the comovement becomes almost triple during the linked period. It appears that the 21-day cumulative returns include the effects from industry factors as it shows relatively stronger correlations between RET21 and industry returns. The earnings news of customer firms has a ripple effect to their suppliers' earnings surprises.

Standardized unexpected earnings (SUE1 and SUE2) offer more direct examination for the comovement of earnings shocks in the firm operations. Derived from a seasonal random walk model, SUE1 and SUE2 are supposed to be randomly distributed. However, in 2-year and 3-year link duration subsample, we find almost same degree of comovement in earnings surprises before and after the CSLs establishment. For the 5-year link duration subsample, we observe the increases in earnings surprises comovement.

As a next, we investigate whether the increases in comovement of stock return and earnings surprises are associated with changes in firms' fundamentals.The long-term customer-supplier relationship is different from a short-term one when we consider the relationship as intangible asset of the firm. In particular, committed long-term customers are valueless assets of the suppliers because business risks can be reduced and shared by these customers. Cooperation does not necessarily align customer and supplier's revenue, but it can also save business networking costs and improve the quality of the profits on both sides. On the other hand, the relationship can be more entranched if the relationship becomes longer. We predict that alignment in fundamentals would be more apparent in longer duration CSLs.

In Table VI, we analyze the comovement in two fundamental variables: profit margin and return on assets (ROA). Similar to equation (1), we replace returns with profit margin and ROA of both dependent (supplier's) and independent variables (customer's). We control the market and industry value-weighted profit margin and ROA.

$$S\_PM_{i,t} = \alpha + \beta^{c} C\_PM_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * C\_PM_{i,t} + \beta^{MKT} MKT\_PM_{t} + \beta^{IND} IND\_PM_{j,t} + \epsilon_{i,t} \quad (7)$$

$$S\_ROA_{i,t} = \alpha + \beta^{c} C\_ROA_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * C\_ROA_{i,t} + \beta^{MKT} MKT\_ROA_{t} + \beta^{IND} IND\_ROA_{j,t} + \epsilon_{i,t} \quad (8)$$

Quarterly and annual fundamental data are retrieved from Compustat. Profit margin is defined as the firm's net income divided by revenue. ROA is defined as the total of income before extraordinary items, interests, and related expenses scaled by total assets. Annual data is more reliable due to the seasonality in accounting variables. Table VI shows that customer and supplier firms have no correlations in the fundamentals when economic links are not formed. After their relationship begins, their profit margins and return on assets become to comove strongly. Profit margins and return on assets are not only the snapshots of a firm's operation but also the indicator of the healthiness of the firm's financials. The comoving fundamentals of customer and supplier firms affirms the existence of the cash flow channel between customer and supplier firms.

Cross-Sectional Determinants of Customer-supplier Return Comovement

In this subsection, we examine the determinants of return comovement between customer and supplier. We regress supplier's weekly returns on customer's weekly returns directly during the linked period and obtain the betas (β). In the second stage regression, we regresses the betas from first stage on a collection of industry, firm, and link characteristics:

I. Industrial comovement, the comovement between supplier's and customer's corresponding industries value-weighted returns.

II. Common institutional ownership, a dummy variable which takes the value of 1 if a customer-supplier pair has at least one common institutional investor, and 0 otherwise.
III. Link duration, the natural log of link duration in months.
IV. Sales concentration, CSL sales divided by supplier/customer's revenue.
V. Accounts payable, the ratio of accounts payable to revenue
VI. Accounts receivable, the ration of accounts receivable to revenue
VII. Size, the natural log of the firm's market capitalization.
VIII. Leverage, firm's total debt scaled by total assets.
IX. Market to book ratio, defined as (total assets + market value of common equity – book value of common equity) / Total assets.
X. ROE, return on equity (net income over equity).
XI. Size difference, the ratio of the supplier firm's market capitalization to customer firm's.

All firm characteristics are from Compustat quarterly file, and institutional ownership data is from CDA/Spectrum. Firm characteristic variables are averaged over the linked period and year fixed effect is applied to the cross-sectional regressions. The revenue, total assets, and common equity which are used forscaling other variables are from the previous fiscal year-end.

In Table VII, we again confirm that a substantial portion of CSL return comovement results from the comovement in industry returns. The evidence among long-term links appears to be strong. Interestingly, common institutional ownership has an explanatory power for the comovement. However, its ability becomes weaker when we control for supplier's firm size. The institutional investors are sophisticated investors, who make the market more efficient. Their trades make the information of one party of CSL incorporated into the stock price of the other party. But for the large supplier, there is less private information left for institutional investors to exploit, hence the common ownership contribute little to the comovement. However, the institutional investors play an essential role in the return comovement between small supplier and customer.

Link duration is a unique variable in CSL comovement study. Influences from some determinants such as investors' behavior are transitory, while others associated with fundamental changes are more permanent. In an unreported subsample analysis, we find the effect of link duration on return comovement is discontinuous. The return comovement is much stronger among long-term links than short-term links.

The first three determinants arerelation specific variables. The rest of the determinants are charicteristics of customers and suppliers. Sales concentration measures the closeness of a customer-supplier relationship. From the supplier's point of view, the transactions are revenues, but they are costs for customers. Our empirical results indicate that customer purchase concentration is the most dominant driver of the comovement, while supplier sales concentration is not significant in most tests. Given the asymmetric nature of customer-supplier network, that size of customer is much larger than size of supplier and customers have more number of CSL than suppliers, customers have more bargaining power than suppliers. When customers can not replace their supplier with another supplier, they have less bargaining power and must share their profits, which leads to more comovement in fundamentals. In unreported results, we find the average supplier sales concentration is around 12%, while the average customer sales concentration is only 0.56%. In a customer-supplier relationship, customers are more likely to take control.

Trade credit is valuable information to companies in the supply chain. It tightens the relationship between customer and supplier by linking some of their financial obligations. We find customer's accounts payable and supplier's account receivable are important determinants of return comovement. Customer's accounts payable is more critical for short-term links, and supplier's accounts receivable are essencial to CSLs of any duration.

Leverage, particularly customer's leverage, provides interesting insights. Leverage represents business risk and financing costs of the company. In table VII, we find that significant coefficient of the supplier's leverage disappears when the size of the supplier is controlled. However, customer's leverage is negatively associated with return comovement. We argue that the leverage of customers allows them to have greater bargaining power against suppliers, but that of suppliers has less effect, because suppliers are more easily replaced by another and thus threatening channels do not work.

In summary, CSL return comovement is greater if the customer and supplier firms are more closely related in terms of their businesses. The proximity of their industries, common institutional ownership, and smaller size differences make them more closely associated. They become more connected to each other if they cooperate for a long-run with substantial sales.

The Aggregation of Idiosyncratic Shocks Through Customer-Supplier Links

Research on idiosyncratic information has received little attention because of the diversification argument. Nevertheless, Campbell, Lettau, Malkiel, and Xu (2001)'s discovery of trending aggregated idiosyncratic volatility in recent decades spotlights the topics and numerous following studies have related the anomaly to various causes (Wei and Zhang 2006, Irvine and Pontiff, 2008, Fink et al. 2009), and delivered different asset pricing implications (Ang, Hodrick, Xing, and Zhang, 2006 and 2009, Han and Lesmond, 2011, Stambaugh, Yu, and Yuan, 2012).

These papers show that idiosyncratic shocks not only play a critical role in valuating corporations which are connected in complex ways, but also affect investors' expectations of firms' risk.

Both theoretical works (Gabaix, 2011, Acemoglu et al., 2012, Kelly, Lustig, and Nieuwerburgh, 2013) and previous empirical results unambiguously suggest the aggregation of idiosyncratic shocks into systematic shock in the customer-supplier network. First of all, customer-supplier network is an asymmetric network. Customers do not hold a business with all their suppliers for the same amount.. Moreover, customers on average are much larger and more powerful than the suppliers, and some customers or suppliers have more businesses with many other firms. Second, our comovement study reveals rich information flows through the links, including earnings news, operating information, and other firm-specific information. These information flows align firms' fundamentals and drive stock return comovement. Idiosycratic shocks to customers should aggregate and become a substantial force that drive the stock prices of their suppliers.

Given the structure of the customer-supplier network, we aim to test if aggregated customers' idiosyncratic shocks are priced in suppliers' returns. We employ Fama and Macbeth two-stage regressions. Customer's idiosyncratic returns are residual in the regression model (6). We include market, size, book-to-market factors, and value-weighted industry return.We aggregate customers idiosyncratic returns by averaging idiosyncratic returns of all customers that have more than three suppliers and generate the customer factor.We first relate the network centrality of the supplier firms and their exposure on customer factor as Ahern (2013) show the importance of centrality in inter-industry network for explaining industry returns. Note that we rule out the industry effects on customer factors by including industry return in the first stage regression to get idiosyncratic return. We first use the number of customers as a proxy for a supplier's network centrality(additional test on the alternative centrality measure is presented in the appendix). We obtain beta of customer factor from the regression of suppliers' returns on customer factor, as well as Fama and French three factors. We then sort companies into six groups by the number of customers of each supplier: suppliers with 1, 2, 3, 4, 5, and more than 5 customers, respectively. Equal-weighted and value-weighted customer betas are calculated for each group.

In Table VIII, we observe that customer betas increase monotonically as the connections of a supplier increase. For suppliers' with only one customer, the value-weighted customer beta is indistinguishable from zero, although the equal-weighted customer beta is statistically significant. When a supplier is in the peripheral of the network, their exposure to aggregated idiosyncratic shock to the customers will be minimal. When a supplier firm is placed more in the center of the customer-supplier network, the correlation between its returns and the customer factor increases extensively. Consistently, for suppliers with more than one customer, both equal-weighted and value-weighted averages of customer betas are highly significant. For suppliers with more than 5 customers, every 1% increase in customer factor will lead to more than 1% increases in their stock returns. The results are consistent with the graunalar network theory. If the firm-specific shocks to customers are not aggregated into systematic shocks rather diversified away, we would not find any exposure of supplier's return to customer factor. Moreover, the pattern that the beta of customer factor increases as the number of supplier's connection would only be observed in the graunalar network. For suppliers with multiple customers, the customer idiosyncratic shocks do aggregate instead of being diversified.

Table IX reports the second stage of Fama-MacBeth regression results. First, we regress suppliers' returns on value-weighted market returns and customer factor and obtain market betas and customer betas using 36-month rolling windows. Next, we run Fama-MacBeth regression of suppliers' returns on customer beta, market beta, as well as four supplier firms' characteristics variables: logged market capitalizations (log(size)), book to market ratio (BM), lagged monthly returns (lag(ret)), and lagged annual returns (lag(ret_1year)), in the month immediately after the 36-month rolling window. We use these firm characteristic variables to control for size, book-to-market, short-term reversal, and momentum effect. Column 1 shows that the coefficient of beta of customer factors is significantly positive. When suppliers are more exposed to customer factors, the return on supplier stocks are significantly higher. One standard deviation increase in beta of customer factor would result in 0.51% increase for average return of supplier. The result implies that aggregate customer risk is not hedgeable to investors and requires a positive risk premium.

In falsification tests (columns 2 and 3), we replace customer factor with aggregated peripheral customers idiosyncratic returns and aggregated market idiosyncratic returns, and find no evidence of pricing. We define peripheral customers as those customer firms with less than three suppliers. Both peripheral customers' Idiosyncratic returns and market Idiosyncratic returns are equal-weighted factors. Not all idiosyncratic returns are aggregated into systematic risks. Non-aggregated idiosyncratic shocks through the customer-supplier network are not priced. The falsification tests once again confirms the shock aggregation through the customer-supplier network. They prove that our results are not driven by the sample biases. In column 4, we include betas for customer factor, peripheral customer factor, and market Idiosyncratic returns at the same time, but only customer factor appears to be priced in the market. In our robustness check, we rerun table IX by using beta of SMB, HML, and UMD as control variables instead of firm characteristics. The results are highly consistent with those reported.

In the appendix, we exmaine the asset pricing implication of network centrality measure. The beta of customer factor is a direct measure of exposure to customer risks for suppliers. However, we can proxy the exposure using the summary statsitic from the structure of the network. We use network centrality concepts to capture the exposure on customer risk. As in Ahern (2013), we use eigenvector centrality of the supplier firms.[8] Eigenvector centrality is defined as the first eigenvector of the customer-supplier network's adjacency matrix.[9] Centrality is not significantly positive, but its magnitude is still economically strong and positive as the theory predicts. Because of the large amount of noise in the customer-supplier network at firm-level data, the centrality measure cannot capture tightly the exposure to customer risk. In addition to Fama-MacBeth regression results, we construct a long-short portfolio based on beta of customer factor. We sort suppliers into quintiles according to their customer betas. Quintile 1 includes the suppliers with the lowest customer betas, while quintile 5 consists of those with highest customer betas. For the long-short portfolio, we buy suppliers with the highest customer betas and sell suppliers with the lowest customer betas simultaneously at the beginning of each month. The portfolio is rebalanced monthly. If we ignore transaction costs and taxes, the long-short portfolio generates annualized equal-weighted alpha of 3.1% and value-weighted alpha of 6.11%, respectively. Our result is more robust for the large suppliers than small suppliers. It is

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[8] Our customer-supplier network is massive and asymmetric. Eigenvector centrality accounts for the importance of a node (firm) for the connectivity in the whole network.

[9] We make the customer-supplier network adjacency matrix using sales number between each firm pair and make the undirectional matrix. For robustness check, we also form an adjacency matrix using dummies to indicate the connections: 1 if two firms are connected and 0 if not. The results from the two methodologies are identical.

less subject to issues on market-microstructures. It shows that investors do get rewarded by bearing customer risk and the return difference is quite sizable.

Conclusion

We scrutinize stock return comovement in customer-supplier relationship. CSL return comovement results from various factors: market influence, industry factors, and investor's attention. The establishment of a customer-supplier relationship amplifies the existing comovement between the two firms. The increase in comovement is primarily due to the cash flow information transmitting between the linked firms. Consistent with the efficient market hypothesis, at least for the long-term customer-supplier relationship, fudamental changes in both firms drives increase in comovement rather than investor's behavior.. Abiding and committed customer-supplier relationships align both firms' fundamentals.

Interestingly, return comovement in CSL comes from idiosyncratic information, instead of the systematic information. Unlike diversification argument, idiosyncratic shocks are propagated through the CSL and stay within the network. The connections and network among firms provide the channel for idiosyncratic shocks to transmit and the power for them to aggregate. The aggregated idiosyncratic shocks eventually become part of the systematic risk of the firms in the network.

The excess returns generated from the long-short portfolio we constructed cannot be explained by Fama and French three factors or momentum factor. It shows that idiosyncratic shocks to the central customers are not diversified away, but are aggregated into the systematic risks. Our result complies with efficient market hypothesis as the customer risk are priced in the market. The risk premium is quite substantial, cannot be ignored when we use any portfolio strategy. Our work provides a important insight of return comovement in the connected firms within the input-output network, and contributes to understanding of the rise of the systematic risk.

Table I

CSL Dataset and CDZ Decompositions Summary Statistics

This table shows the summary statistics of our customer-supplier links (CSL) collection. The dataset includes all the principal customers reported by supplier firms. The sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX. Utility firms and financial institutions are excluded as well as ADRs. We also exclude micro stocks whose prices are lower than $5. The sample period spans from 1980 to 2015. Quarterly return decomposition uses the approach proposed by Chen, Da, and Zhao (CDZ, 2013). The model use analyst earnings forecasts as direct measures of expected cash flows (CF) to backs out the discount rate (DR) estimates. Both CF news and DR news are winsorized to 5 and 95 percentiles.

Panel A: Link Summary					
Number of suppliers			6492		
Number of customers			2902		
Number of links			18088		
Number of links in the same industry			2976		
Panel B: Link and CDZ Decompositions Statistics					
	MIN	MAX	MEAN	MEDIAN	STD
Number of suppliers per year	389	1215	978.3	1029	175.7
Number of customers per year	344	1069	828.0	920	186.5
Number of links per year	617	2514	1801.8	1949	497.3
Number of links in the same industry per year	42	394	254.0	288	101.6
Link durations (years)	1	34	6.3	5	5.2
Number of customers per supplier	1	36	2.6	2	2.4
Number of suppliers per customer	1	450	6.2	1	18.8
Customer size (in millions, USD)	5.81	724773.40	37106.19	10336.55	67148.99
Supplier size (in millions, USD)	2.44	275006.06	2330.90	285.03	11093.95
Customer returns (weekly, %)	-83.76	130.70	0.89	0.56	5.29
Supplier returns (weekly, %)	-61.17	91.67	1.21	0.55	7.27
Returns (Excluding Dividends)	-96.85%	315.46%	2.32%	2.03%	18.29%
CF News	-42.78%	45.03%	1.01%	0.66%	18.29%
DR News	-119.99%	358.24%	1.20%	0.52%	24.25%
Panel C: CSL's Cross-Sectional Statistics					
Number of suppliers per customer per year	1	2	3	4	5
Count	10424	2875	1484	945	654
Percentage	57.63%	15.89%	8.20%	5.22%	3.62%
Number of customers per supplier per year	1	2	3	4	5
Count	10160	4271	1986	645	252
Percentage	56.17%	23.61%	10.98%	3.57%	1.39%
Link Duration	1-year	2-year	3-year	5-year	8-year
Count	6832	3314	2175	990	371
Percentage	37.77%	18.32%	12.02%	5.47%	2.05%
Link Duration	>=1 year	>=2 year	>=3 year	>=4 year	>=5 year
Count	18088	11229	7890	4260	1985
Percentage	100.00%	62.08%	43.62%	23.55%	10.97%

Table II
Pair-wise Changes in Co-movement of Supplier and Customer

We estimate the following model:

$$SRET_{i,t} = \alpha + \beta^{c} CRET_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * CRET_{i,t} + \beta^{MKT} MKT_{t} + \beta^{IND} IND_{j,t} + \epsilon_{i,t}$$

The dependent variable $SRET_{i,t}$ is returns of suppliers. $CRET_{i,t}$ is a corresponding customer's weekly returns. $Link_{i,t}$ is dummy variable which takes the value of 1 if two firms are linked as customer and supplier at the time of observation, and 0 otherwise. We impose a two-year gap between linked and unlinked period. $Link*CRET_{i,t}$ is the interaction term. We estimate a balanced panel model for each link duration subset. E.g., for all links last longer than 2 years, (t-208, t-104) weeks is the unlinked period while (t, t+104) weeks is the linked period. MKT_t is the value-weighted weekly market returns and $IND_{j,t}$ is value weighted weekly returns of supplier's corresponding industry, defined by Fama and French 48 industry classification. Both indices exclude the corresponding supplier firm. This sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX, with prices no less than $5. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and are adjusted by industry clustered standard errors. CF news and DR news are decomposed quarterly returns of customer firms. Quarterly return decomposition uses the approach proposed by Chen, Da, and Zhao (CDZ, 2013). Both CF news and DR news are winsorized to 5 and 95 percentiles.

	Changes in Comovement								
CRET	Panel A: Returns			Panel B: CF News			Panel C: DR News		
Link Duration	2-year	3-year	5-year	2-year	3-year	5-year	2-year	3-year	5-year
CRET	0.078***	0.080***	0.080***	0.064***	0.048***	0.007	0.061**	0.066**	0.090***
	(9.22)	(8.86)	(6.80)	(4.26)	(3.36)	(0.58)	(2.46)	(2.64)	(5.04)
Link	-0.000**	-0.000	-0.000**	-0.008	-0.004	-0.011*	-0.019**	-0.016**	-0.015**
	(-2.42)	(-1.40)	(-2.06)	(-1.61)	(-0.87)	(-1.72)	(-2.31)	(-2.37)	(-2.24)
Link_CRET	0.022***	0.018**	0.021**	-0.020	-0.004	0.046***	0.000	-0.021	-0.028
	(2.93)	(2.18)	(2.18)	(-1.31)	(-0.21)	(3.29)	(0.00)	(-0.80)	(-1.39)
MKT	0.112***	0.112***	0.133***	-0.034	-0.032	-0.080	0.285***	0.275***	0.269***
	(3.13)	(2.90)	(3.29)	(-0.54)	(-0.52)	(-1.15)	(5.23)	(5.23)	(5.27)
IND	0.908***	0.894***	0.868***	-0.157**	-0.150**	-0.137**	0.533***	0.517***	0.503***
	(21.22)	(20.37)	(20.24)	(-2.47)	(-2.40)	(-2.15)	(13.07)	(13.03)	(12.47)
Constant	-0.000	-0.000**	-0.000	0.059***	0.055***	0.062***	0.034***	0.034***	0.035***
	(-1.56)	(-2.29)	(-1.30)	(9.76)	(8.69)	(8.39)	(4.06)	(4.95)	(5.06)
Observations	679,572	773,304	752,984	76,863	72,360	59,257	76,863	72,360	59,257
Adjusted R^2	0.182	0.180	0.183	0.004	0.004	0.005	0.164	0.161	0.169
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table III

Pair-wise Changes in Co-movement of Real Supplier (Pseudo Supplier) and Pseudo Customer (Real Customer)

We estimate the following model:

$$\text{Panel A: } SRET_{i,t} = \alpha + \beta^{c} PCRET_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * PCRET_{i,t} + \beta^{MKT} MKT_{t} + \beta^{IND} IND_{j,t} + \epsilon_{i,t}$$

$$\text{Panel B: } PSRET_{i,t} = \alpha + \beta^{c} CRET_{i,t} + \gamma^{link} Link_{i,t} + \beta^{LC} Link * CRET_{i,t} + \beta^{MKT} MKT_{t} + \beta^{IND} IND_{j,t} + \epsilon_{i,t}$$

For each customer (supplier) firm in the CSL dataset, we randomly identify a matched firm within the same stock exchange, the same size quintile categorized by NYSE common stock breakpoints, and the same industry defined by Fama and French 48 industry classification. The dependent variable $SRET_{i,t}$ is returns of suppliers. $PCRET_{i,t}$ is a corresponding pseudo customer's weekly returns. $CRET_{i,t}$ is a customer's returns. $PSRET_{i,t}$ is a corresponding pseudo supplier's weekly returns. $Link_{i,t}$ is dummy variable which takes the value of 1 if two firms are linked as real customer and supplier at the time of observation, and 0 otherwise. We impose a two-year gap between linked and unlinked period. We estimate a balanced panel model for each link duration subset. E.g., for all links last longer than 2 years, (t-208, t-104) weeks is the unlinked period while (t, t+104) weeks is the linked period. MKT_t is the value-weighted weekly market returns and $IND_{j,t}$ is value weighted weekly returns of supplier's corresponding industry, defined by Fama and French 48 industry classification. Both indices exclude the corresponding supplier firm. This sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX, with prices no less than \$5. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and are adjusted by industry clustered standard errors. CF news and DR news are decomposed quarterly returns of customer firms. Quarterly return decomposition uses the approach proposed by Chen, Da, and Zhao (CDZ, 2013). Both CF news and DR news are winsorized to 5 and 95 percentiles.

Psuedo Customer									
CRET	Returns (Weekly)			CF News (Quarterly)			DR News (Quarterly)		
Link Duration	2-year	3-year	5-year	2-year	3-year	5-year	2-year	3-year	5-year
CRET	0.067***	0.058***	0.064***	0.026	0.054**	0.017	0.044**	0.044**	0.042**
	(9.39)	(5.36)	(7.50)	(1.23)	(2.61)	(0.55)	(2.64)	(2.56)	(2.64)
Link	-0.000*	-0.001***	-0.001***	-0.005	0.004	-0.011**	-0.003	0.002	0.002
	(-1.97)	(-4.29)	(-3.02)	(-1.32)	(0.87)	(-2.16)	(-0.93)	(0.63)	(0.26)
Link_CRET	-0.011	-0.009	-0.013*	0.017	-0.013	0.032	-0.028	-0.016	-0.019
	(-1.68)	(-0.87)	(-1.76)	(0.53)	(-0.46)	(1.04)	(-1.39)	(-1.27)	(-1.29)
MKT	0.173***	0.180***	0.175***	-0.041	0.003	-0.049	0.203***	0.197***	0.215***
	(6.83)	(5.60)	(5.33)	(-0.58)	(0.05)	(-0.70)	(4.50)	(4.29)	(4.42)
IND	0.755***	0.774***	0.743***	-0.146***	-0.178***	-0.171***	0.450***	0.448***	0.438***
	(20.83)	(20.87)	(22.39)	(-2.76)	(-3.52)	(-2.95)	(10.30)	(8.59)	(9.45)
Constant	0.000	0.000	0.000	0.054***	0.044***	0.060***	0.037***	0.033***	0.031***
	(0.47)	(0.15)	(1.53)	(11.45)	(8.58)	(9.86)	(8.70)	(10.84)	(5.88)
Observations	403,896	449,759	453,336	35,107	31,220	26,705	35,669	32,156	26,403
Adjusted R^2	0.162	0.172	0.164	0.004	0.005	0.006	0.145	0.147	0.148
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Psuedo Supplier								
CRET	Returns (Weekly)			CF News (Quarterly)			DR News (Quarterly)		
Link Duration	2-year	3-year	5-year	2-year	3-year	5-year	2-year	3-year	5-year
CRET	0.045***	0.049***	0.050***	0.045**	0.066**	0.050**	0.004	-0.002	0.011
	(5.81)	(5.18)	(5.10)	(2.50)	(2.61)	(2.23)	(0.26)	(-0.11)	(0.52)
Link	-0.001**	-0.000	-0.001***	0.001	-0.004	-0.012**	0.001	-0.001	-0.008*
	(-2.24)	(-0.47)	(-3.04)	(0.14)	(-0.74)	(-2.26)	(0.36)	(-0.14)	(-1.72)
Link_CRET	-0.011	0.002	0.004	0.004	-0.027	-0.008	-0.008	-0.007	-0.010
	(-1.26)	(0.38)	(0.47)	(0.24)	(-1.12)	(-0.33)	(-0.62)	(-0.51)	(-0.57)
MKT	0.197***	0.177***	0.195***	0.049	0.082	0.041	0.145***	0.137***	0.143***
	(5.65)	(5.58)	(6.74)	(0.62)	(0.89)	(0.41)	(4.14)	(3.76)	(4.82)
IND	0.810***	0.800***	0.774***	-0.169***	-0.176***	-0.166***	0.491***	0.539***	0.510***
	(17.53)	(19.86)	(23.20)	(-2.87)	(-3.19)	(-2.80)	(13.57)	(14.60)	(13.40)
Constant	-0.000	-0.000***	-0.000	0.044***	0.048***	0.056***	0.030***	0.032***	0.039***
	(-1.52)	(-3.53)	(-0.67)	(8.62)	(8.17)	(9.50)	(9.46)	(8.37)	(8.89)
Observations	318,968	373,543	406,323	34,094	30,780	27,058	32,234	29,938	26,194
Adjusted R^2	0.186	0.178	0.174	0.005	0.004	0.004	0.156	0.172	0.156
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IV

Idiosyncratic and Systematic Returns Comovement

We decompose both customer and supplier's monthly excess returns into idiosyncratic and systematic components using Fama and French three-factor model, plus controlling for value weighted industry returns. Excess returns are calculated by subtracting the U.S. T-bill rate. Our model uses the 60-month rolling window to regress a firm's monthly returns on the Fama and French three factors (MKTRF, HML, and SMB) as well as its corresponding industry's value-weighted returns to predict its next month's return. The predicted return is the systematic return and the prediction error is the idiosyncratic return. The dependent variable is supplier's idiosyncratic/systematic return, and CRET is customer's idiosyncratic/systematic return. Link is a dummy variable which takes the value of 1 if two firms are linked as real customer and supplier at the time of observation, and 0 otherwise. We estimate a balanced panel model for each link duration subset. E.g., for all links last longer than 2 years, (t-48, t-24) months is the unlinked period while (t, t+24) months is the linked period. MKT is the value-weighted market idiosyncratic/systematic returns and IND is value weighted idiosyncratic/systematic returns of supplier's corresponding industry, defined by Fama and French 48 industry classification. Both indices exclude the corresponding supplier firm. This sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX, with prices no less than $5. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and are adjusted by industry clustered standard errors.

Idiosyncratic and Systematic Returns Comovement						
CRET	IdioRet			SysRet		
Link Duration	2-year	3-year	5-year	2-year	3-year	5-year
CRET	0.058***	0.038***	0.039***	0.138***	0.134***	0.118***
	(3.30)	(2.71)	(3.36)	(4.20)	(4.40)	(3.59)
Link	-0.001	-0.000	-0.001	0.001	0.000	0.001
	(-0.43)	(-0.24)	(-0.77)	(1.07)	(0.68)	(1.28)
Link_CRET	0.008	0.038***	0.031***	-0.001	-0.009	0.015
	(0.48)	(3.11)	(3.22)	(-0.07)	(-0.52)	(1.13)
MKT	1.196***	1.275***	1.225***	0.465***	0.449***	0.416***
	(4.95)	(5.61)	(6.41)	(4.88)	(5.17)	(5.29)
IND	0.018	0.029	0.145*	0.621***	0.625***	0.631***
	(0.19)	(0.32)	(1.69)	(9.09)	(10.53)	(11.49)
Constant	-0.004***	-0.005***	-0.005***	0.002**	0.002**	0.001**
	(-4.01)	(-4.98)	(-4.84)	(2.53)	(2.55)	(2.49)
Observations	125,033	148,621	160,917	125,033	148,621	160,917
Adjusted R^2	0.003	0.004	0.004	0.486	0.491	0.507
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table V

Comovement in Earnings Surprises

This table presents the comovement between supplier and customer firm's earnings surprises. We use four earnings surprises measurement: Ret5 and Ret21 respectively are post-earnings announcement 5-day and 21-day returns. We match supplier's earnings announcement date to its customer's in each reporting quarter. Sue1 is earnings surprises measured using a rolling seasonal random walk model (Livnat and Mendenhall, 2006). Sue2 is Sue1 accounting for the exclusion of special items. The dependent variable is supplier's earnings surprises, the ES is customer's earnings surprises. Link is a dummy variable which takes the value of 1 if two firms are linked as real customer and supplier at the time of observation, and 0 otherwise. We estimate a balanced panel model for each link duration subset. E.g., for all links last longer than 5 years, (t-84, t-24) months is the unlinked period while (t, t+60) months is the linked period. MKT is the value-weighted market earnings surprises and IND is value weighted earnings surprises of supplier's corresponding industry, defined by Fama and French 48 industry classification. Both indices exclude the corresponding supplier firm. This sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX, with prices no less than \$5. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and are adjusted by industry clustered standard errors.

ES Measure	Ret5			Ret21			Sue1			Sue2		
	2-year	3-year	5-year	2-year	3-year	5-year	2-year	3-year	5-year	2-year	3-year	5-year
ES	0.016	-0.012	-0.001	0.071**	0.056**	0.083***	0.080***	0.058**	0.020	0.090***	0.068***	0.031*
	(0.42)	(-0.42)	(-0.04)	(2.52)	(2.67)	(4.54)	(3.72)	(2.46)	(1.02)	(4.36)	(3.15)	(1.95)
Link	-0.003	-0.005**	-0.002	-0.004	-0.009***	-0.003	-0.002	-0.002	-0.003***	-0.001	-0.001	-0.002***
	(-1.22)	(-2.45)	(-0.83)	(-1.58)	(-3.15)	(-0.98)	(-1.33)	(-1.37)	(-3.27)	(-1.13)	(-1.33)	(-2.86)
Link_ES	0.051	0.091**	0.109***	0.137***	0.143***	0.106***	-0.042	-0.009	0.061***	-0.047**	-0.021	0.049**
	(1.10)	(2.57)	(3.29)	(3.05)	(3.61)	(2.90)	(-1.57)	(-0.40)	(3.44)	(-2.21)	(-1.02)	(2.35)
MKT_ES	0.813***	0.639***	0.690***	0.354***	0.328***	0.356**	0.680***	0.594**	0.614***	0.418*	0.431**	0.418**
	(3.27)	(2.81)	(3.40)	(3.47)	(2.75)	(2.39)	(2.88)	(2.53)	(2.95)	(1.98)	(2.20)	(2.56)
IND_ES	0.660***	0.644***	0.531***	0.839***	0.789***	0.652***	0.730***	0.714***	0.671***	0.762***	0.740***	0.696***
	(4.47)	(4.67)	(4.72)	(9.92)	(7.95)	(4.91)	(6.58)	(6.10)	(7.71)	(6.53)	(6.74)	(10.84)
Constant	0.003	0.004*	0.004	-0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.001
	(1.18)	(1.87)	(1.49)	(-0.36)	(0.41)	(0.31)	(0.12)	(0.06)	(1.43)	(0.15)	(0.11)	(1.37)
Observations	47,908	48,578	42,319	47,833	48,508	42,270	55,528	56,875	49,910	55,615	56,970	49,984
Adjusted R^2	0.045	0.042	0.041	0.199	0.183	0.161	0.036	0.035	0.039	0.035	0.036	0.040
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VI
Comovement in Fundamentals

We estimate the comovement in profit margin (PM) and return on total assets (ROA). PM is net income scaled by firm's revenue. ROA is the total of income before extraordinary items and interests and related expenses divided by lagged total assets. Fundamentals date comes from Compustat's annual update database. We regress suppliers' fundamental variables on customers'. C_Var is a corresponding customer's PM and ROA. $Link_{i,t}$ is dummy variable which takes the value of 1 if two firms are linked at the time of observation, and 0 otherwise. We estimate a balanced panel model for each link duration subset. E.g., for all links last longer than 5 years, (t-84, t-24) months is the unlinked period while (t, t+60) months is the linked period. MKT_Var is the value-weighted quarterly marketwide PM and ROA, and IND_Var is value weighted annual PM and ROA of supplier's corresponding industry, defined by Fama and French 48 industry classification. This sample comprises of common stocks listed at NYSE, NASDAQ, and AMEX, with annual sales no less than $10 million. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and are adjusted by industry clustered standard errors.

Comovement in Fundamentals						
	2-year		3-year		5-year	
Var	PM	ROA	PM	ROA	PM	ROA
C_Var	-0.078	-0.058	-0.132***	-0.057	-0.086*	-0.082
	(-0.96)	(-0.87)	(-3.34)	(-0.98)	(-1.90)	(-1.26)
Link	-0.018**	-0.021***	-0.025***	-0.022***	-0.011	-0.023***
	(-2.15)	(-3.88)	(-3.77)	(-4.66)	(-1.12)	(-4.36)
Link*C_Var	0.214***	0.112**	0.288***	0.116***	0.138**	0.099**
	(3.96)	(2.03)	(7.01)	(3.23)	(2.28)	(2.08)
MKT_Var	0.072	0.093	-0.323	-0.064	-0.591	-0.057
	(0.30)	(0.52)	(-0.90)	(-0.47)	(-1.45)	(-0.35)
IND_Var	1.517***	1.272***	1.461***	1.263***	1.351***	1.159***
	(8.03)	(6.40)	(6.25)	(5.28)	(5.41)	(5.19)
Constant	-0.003	-0.013	0.043	0.007	0.067**	0.021
	(-0.12)	(-1.00)	(1.38)	(0.55)	(2.17)	(1.51)
Number of observations	13,300	11,103	12,130	10,220	9,310	7,973
Adjusted R^2	0.215	0.140	0.204	0.145	0.184	0.137
Industry Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Firm Characteristics Determinants of Comovement

This table investigates the determinants of CSL comovement. The dependent variable is the direct comovement between supplier and customer firms during the linked period. Industry comovement is the comovement between supplier and customer's industries, defined by Fama and French 48 industry classifications. Institutional ownership overlap is a dummy variable that takes a value of 1 if customer and supplier firms see more than one common institutional investor, and 0 otherwise. Link duration is the natural log of the link duration in months. Size is the natural log of firm's market capitalizations. Sales concentration is CS sales divided by the revenue of either supplier or customer firm. Payable is accounts payable to revenue ratio. Receivable is accounts receivable to revenue ratio. Leverage is total debt scaled by firm's total assets. Market to book ratio is market value of the total assets divided by book value of firm's total assets. ROE is net income scaled by market value of the equity. Size difference is supplier's size scaled by customer's size. All independent variables are averaged over the duration of the linked period. This sample includes common stocks listed at NYSE, NASDAQ, and AMEX, with prices no less than $5. Utility firms, financial institutions, and ADRs are excluded. Sample period spans from 1980 to 2015. T-stats are presented in parentheses and year fixed effect are applied to all regressions.

	Panel A: Full Sample				Panel B: Long-term Links			
Model	1	2	3	4	1	2	3	4
Industry Comovement	0.095***	0.096***	0.136***	0.134***	0.293***	0.244***	0.277***	0.253***
	(8.32)	(6.96)	(8.67)	(9.49)	(11.50)	(8.65)	(10.04)	(9.92)
Inst. Ownership Overlap	0.040***	0.009	0.024*	0.059***	0.039***	0.003	0.013	0.049***
	(3.46)	(0.69)	(1.76)	(4.98)	(2.65)	(0.19)	(0.84)	(3.38)
Link Duration	0.014***	0.013**	0.007	0.019***	0.028**	0.017	0.006	0.065***
	(2.76)	(2.43)	(1.19)	(3.73)	(2.07)	(1.11)	(0.37)	(4.77)
C_sales concentration	0.988***		0.537**		1.483***		0.958*	
	(4.76)		(2.15)		(3.39)		(1.86)	
C_payable	0.242***		0.251***	0.202**	0.146		0.231*	0.183
	(2.97)		(2.58)	(2.30)	(1.28)		(1.84)	(1.58)
C_size	0.034***		0.029***		0.040***		0.034***	
	(13.58)		(9.55)		(11.32)		(8.85)	
C_leverage	-0.190***		-0.210***	-0.159***	-0.199***		-0.238***	-0.211***
	(-7.15)		(-6.80)	(-5.66)	(-5.10)		(-5.54)	(-5.46)
C_mb	0.008**		0.010**	0.011***	-0.007		-0.004	-0.005
	(2.37)		(2.51)	(3.14)	(-1.04)		(-0.55)	(-0.83)
C_roe	-0.039**		-0.046**	-0.009	-0.028		-0.019	0.052**
	(-2.00)		(-2.05)	(-0.45)	(-1.14)		(-0.74)	(2.36)
S_sales concentration		0.078**	-0.007			-0.001	-0.057	
		(1.98)	(-0.16)			(-0.02)	(-1.07)	
S_receivable		0.066**	0.070**	0.090***		0.166***	0.109**	0.107***
		(2.33)	(2.30)	(3.35)		(3.31)	(2.21)	(2.60)
S_size		0.034***	0.029***			0.025***	0.021***	
		(13.98)	(11.02)			(8.71)	(7.10)	
S_leverage		-0.012	0.015	0.043**		0.037	0.060**	0.099***
		(-0.67)	(0.80)	(2.51)		(1.41)	(2.28)	(4.13)
S_mb		0.002	0.002	0.001		0.009***	0.011***	0.009***
		(1.38)	(1.48)	(0.53)		(2.60)	(3.07)	(2.61)
S_roe		-0.032***	-0.041***	-0.019**		-0.063***	-0.062***	-0.041***
		(-3.95)	(-4.72)	(-2.40)		(-5.75)	(-5.75)	(-4.24)
Size difference				-0.025***				-0.027***
				(-4.62)				(-3.12)
Constant	-0.122***	-0.024	-0.260***	0.191***	-0.369***	-0.138*	-0.380***	-0.098
	(-2.96)	(-0.72)	(-5.13)	(5.76)	(-4.58)	(-1.74)	(-4.25)	(-1.32)
Observations	5,321	3,816	3,297	4,409	2,222	1,868	1,748	2,210
Adjusted R^2	0.064	0.068	0.125	0.051	0.128	0.110	0.188	0.095
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VIII

One-way Sorted Customer Betas

This table presents one-way sort portfolios based on customer betas (betas of aggregated customer idiosyncratic returns). Customer idiosyncratic returns are the residuals backed out from a customer firm's monthly excess return using a model controlling for Fama and French 3 factors (MKTRF, SMB, and HML) in addition to its corresponding value weighted industry mean returns. We group the customer betas into 6 groups by the number of customers of each supplier firm. Group 1-5 are supplier firms with 1-5 customer firms, respectively. Group 6 hosts supplier firms with more than 5 customer firms. Customer betas are estimated in the first step of Fama-Macbeth methodology using 36-month rolling windows. This first step regress supplier firms' returns on aggregated customer idiosyncratic returns, as well as Fama and French three factors. Both equal-weighted and value-weighted customer betas are shown in the table. The sample includes common stocks listed at NYSE, NASDAQ, and AMEX. Utility firms, financial institutions, microcap stocks (stock prices lower than $5), and ADRs are excluded.

Group: Number of Customers	Customer Beta EW	Customer Beta VW
1	24.1***	1.23
	(13.6)	(0.74)
2	49.12***	17.09***
	(17.41)	(4.93)
3	26.21***	20.23***
	(7.95)	(4.92)
4	48.24***	54.87***
	(8.17)	(11.54)
5	101.76***	86.57***
	(6.6)	(5.49)
6	105.02***	120.93***
	(9.61)	(10.5)

Table IX

Customer Risk Factor

This table includes the test results on whether the customer factor is priced in supplier's stock returns. Customer factor is monthly aggregated idiosyncratic returns of all customers in our sample. Idiosyncratic returns are the residuals backed out from a firm's monthly excess return using a model controlling for Fama and French 3 factors (MKTRF, SMB, and HML) in addition to its corresponding value weighted industry mean returns. Peripheral customers are customer firms with less than 3 suppliers in our sample. Size is a firm's market capitalization in the previous month. BM is calculated as current fiscal year's book equity to the firm's market equity in June. All stock returns are matched with BM from previous fiscal year. The regressions also controls for lag monthly (lag(RET)) and annual returns (Lag(RET_1Year)). The regressions follow Fama-Macbeth methodology. Betas of each independent variable are first estimated using the 36-month rolling window in the first step. The second step runs cross-sectional regression of supplier returns on each as well as all betas in the months immediately following the rolling windows. The sample includes common stocks listed at NYSE, NASDAQ, and AMEX. Utility firms, financial institutions, microcap stocks (stock prices lower than $5), and ADRs are excluded.

Customer Factor	0.0616***			0.0507***
	(3.19)			(2.77)
Peripheral Customers Idiosyncratic Returns		-0.314		0.0853
		(-0.82)		(1.53)
Market Idiosyncratic Returns			0.0170	0.0237
			(0.75)	(1.09)
MKTRF	-0.126	0.0790	-0.112	-0.132
	(-0.80)	(0.32)	(-0.71)	(-0.85)
Log(Size)	-0.114***	0.0349	-0.0933***	-0.124***
	(-3.45)	(0.24)	(-2.69)	(-3.63)
BM	0.250	2.320	0.268	0.0826*
	(1.49)	(1.04)	(1.53)	(1.82)
Lag(RET)	-3.430***	-1.500	-3.760***	-3.910***
	(-5.74)	(-0.64)	(-6.64)	(-6.87)
Lag(RET_1Year)	0.459*	1.420	0.390**	0.362**
	(1.96)	(1.25)	(2.00)	(2.01)
Constant	1.410***	-1.030	1.210***	1.570***
	(4.04)	(-0.41)	(3.14)	(4.49)
Number of Observations	180960	180960	180960	180960
Adjusted R^2	0.072	0.072	0.072	0.083

Table X

Long-short Portfolio

We construct a long-short portfolio to profit from customer-supplier network risk propagation. This table presents the excess returns from our long-short portfolio strategy. Supplier firms are first sorted into quintiles based on their customer betas: 1 being the lowest customer beta group and 5 being the highest beta group. The dependent variable of the long-short portfolio is the differences in supplier returns between group 5 and group 1. RetEW and RetVW are simply the equal-weighted and value-weighted stock returns of the supplier firms in each quintile. We employ Fama and French 4-factor model to evaluate the risk compensation. AlphaEW and AlphaVW are intercepts from regressions of equal-weighted and value-weighted supplier returns on the 4 factors (MKTRF, SMB, HML, and UMD). The sample includes common stocks listed at NYSE, NASDAQ, and AMEX. Utility firms, financial institutions, microcap stocks (stock prices lower than $5), and ADRs are excluded.

Customer Beta Quintiles	RetEW	RetVW	AlphaEW	AlphaVW
1	1.23***	0.83***	0.21**	-0.14
	(3.91)	(2.65)	(2.08)	(-0.9)
2	1.24***	0.96***	0.18**	0.07
	(4.9)	(4.36)	(2.21)	(0.65)
3	1.26***	0.91***	0.23***	0.05
	(5.09)	(4.07)	(3.38)	(0.48)
4	1.39***	0.98***	0.35***	0.16
	(5.18)	(3.34)	(4.33)	(1.07)
5	1.51***	1.3***	0.47***	0.37**
	(4.55)	(3.75)	(4.31)	(2.17)
Long-Short Portfolio	0.28**	0.47**	0.26*	0.51**
	(2.18)	(2.17)	(1.95)	(2.28)
Annualized Alpha	3.34**	5.68**	3.1*	6.11**
	(2.18)	(2.17)	(1.95)	(2.28)

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Essay 2

Economic Outcomes of Corporate Espionage

Abstract

This paper investigates the economic outcomes of corporate espionage (also known as trade secrets) lawsuits. Utilizing 137 hand-collected trade secret cases, we find significantly positive (negative) abnormal returns for the favorable (unfavorable) court decisions up to 5 days around the court decision dates. Our findings are consistent with two hypotheses: information leaking before the event and investor overreaction/underreaction on and after the event days. Our analysis on firm fundamentals show that the consequences of losing trade secret lawsuits are long-lasting. The findings indicate that the punishment incorporated by the market is more severe for the losing firms.

Introduction

The stock market is susceptible to companies' involvement in legal confronts. Corporate litigations are expensive, and affect a firm's stock market performance as well as corporate decisions. Karpoff et al. (2008a) show that a firm's reputational damage from financial misrepresentation can be 7.5 times as large as the nominal penalty from the law enforcement order. Moreover, the managers personally must pay the price for cooking the book (Karpoff et al. 2008b). Extensive studies have focused on the consequences of firms' malpractice, which is against public interests (Becker, 1968; Alexander, 1999; Karpoff et al. 2008a, 2008b; Karpoff et al. 2005; Karpoff et al. 2014). Nevertheless, little attention has been paid to the economic outcomes of legal battles over sensitive corporate issues, such as corporate espionage, between companies. Corporate espionage, emerged from intense market competition and intended to steal the trade secrets from competing firms, implies lucrative opportunities and dramatic conflicts of interests (Fink, 2003; Fitzpatrick, 2003; Fitzpatrick et al., 2004). The resolutions of such corporate espionage cases have important economic implications.

In this paper, we seek to fill this gap by examining the financial outcomes of firms embattled in corporate trade secret lawsuits. Corporate espionage activities are widely studied in legal and ethical areas (Boni, 1999; Maher and Thompson, 2002; Almeling et al., 2009, 2010), but little has been explored on the business side. Thus, the purpose of this paper is to supplement the trade secret research with insights from the financial market.

Using hand-collected trade secret lawsuits from the LexisNexis database for the period of 1992 to 2012, we find that when a court decision is favorable (unfavorable) to a firm, the firm's market-adjusted returns are significantly positive (negative). The abnormal returns last for a five-day event window (-2, 2). The results shed lights on the trading behavior of investors. Anecdotal evidence shows that active investors attempt to dig the leaking information and trade accordingly. Moreover, Eastwood and Nutt (1999) and Chan (2003) show that investors overreact to good news and underreact to bad news. The empirical evidence we document supports both information leaking and investor overreaction/underreaction hypotheses. We further show that the impacts of the trade secret lawsuits are long-lasting, especially for firms losing the case. The evidence indicates that the punishment borne by the market is more substantial for firms losing the litigations.

Our paper makes several contributions to the literature. First, our study contributes to the legal research in the financial market. Karpoff et al. (2008a, 2008b) show that the costs of firms cooking the books are enormous, including reputational loss and direct penalty. We provide evidence on the economic consequences of trade secret lawsuits. We add to the literature by analyzing how the court decisions of legal combats over corporate trade secret activities affect investors' expectation of the firms in the short run.

Second, our work also contributes to documenting how the court decisions influence a firm's corporate activities in the long run. Gurun and Kominers (2014) show that intellectual rights lawsuits, such as patent trolls, discourage future innovation activities of the target firms. We add to the literature by showing that this discouragement is not only for patent troll cases. In addition, we find that firms losing the trade secret cases tend to be more conservative in their corporate activities with fewer intangible assets, lower capital expenditures, and less use of debt. The rest of the paper is organized as follows. Section 2 describes data and methodology. Section 3 presents the empirical results of the event study. Section 4 illustrates the implications for corporate policies. Section 5 concludes the paper.

Data and Methodology

The data used in this paper is composed of hand-collected trade secret cases from LexisNexis Academic. Cases in our sample generally go through at least two court trials before they conclude. Since our paper investigates the economic outcomes, we exclude cases with no public firms involved. Our initial sample consists of 213 cases for the period of 1992 to 2012. The 213 cases cover 569 trials. We collect a set of information for each trial including names, GVKEYs, and CUSIPs of both plaintiff and defendant companies. We then match the firms with the data in CRSP and Compustat. For each trial in each case, we also identify the favorability of the court rulings to both parties. There are trials deemed as non-material, which are thus excluded in later analysis. Reasons to classify the non-material cases are summarized in detail in Appendix Table A1.

Table 1 presents the summary of the cases collected. One lawsuit case goes through roughly five trials before it concludes. Most cases conclude after two trials. After excluding trials with non-material court decisions and those without available return data, our final sample is composed of 137 cases that cover 312 trials.

All trials in the final sample are categorized into two groups: 1) plaintiff group, which are in pursuit of recovering their damages actively; 2) defendant group, which fights to secure their benefits. The trials in each group are further assigned to three categories based on court decisions: favorable, unfavorable, or non-material. As shown in Table 1, we identify 57 trials that favor plaintiffs, 68 favor defendants, 31 against plaintiffs, 58 against defendants, and 98 non-material decisions. This hand-collected dataset allows us to observe the stock market reactions to material court decisions from one side of the lawsuits because either the return data for the other side is not available or the other side is not a public company.

We follow Karpoff et al. (2009) and conduct an event study on the market reaction to trade secret lawsuit decisions. Abnormal returns are estimated based on the market model during short-term event windows around material decision announcement dates. We compute the cumulative raw returns (CRET) and the cumulative abnormal returns (CAR) on the event day (0), one (-1, 1), and two trading days (-2, 2) around the decision announcement dates.

Empirical Results

Prior studies document significantly positive returns around good news events, such as earnings announcements and earnings surprises (La Porta et al., 1986; DeFond et al., 2007). Thus, we expect to observe positive price reaction to favorable court decisions. On the other hand, when they receive unfavorable court rulings, firms are expected to experience negative stock price movement (Karpoff et al., 2008). In addition, firms experience reputation loss when they have product recalls (Jarrell and Peltzman, 1985), defense procurement fraud (Karpoff et al., 1999), and environmental violations (Karpoff, et al., 2005).

Table 2 reports the stock market reaction around the court decision dates in our sample. We form six categories: Plaintiffs (Favorable), Plaintiffs (Unfavorable), Defendants (Favorable), Defendants (Unfavorable), Plaintiffs (Non-material), and Defendants (Non-material). As reported in Panel A of Table 2, the mean CAR ranges from -1.739% to 2.284% for the six categories. When plaintiffs receive favorable court decisions, 85.96% out of the 57 firms experience positive abnormal returns. In the case of Plaintiffs (Favorable), the average CAR is 2.284% with a Patell's t value of 4.30. Similarly, when the court decisions for defendants are favorable, the abnormal returns are also significantly positive (2.171%). Both results are consistent with prior studies and our predictions that firms benefit from favorable court rulings, resulting in positive stock market reaction. In contrast, the mean event day CAR is significantly negative when court rulings are unfavorable for both plaintiffs and defendants with values of -1.365% and -1.739%, respectively. Unfavorable decisions discourage investors' confidence, which further reduces a firm's market valuation. The mean CAR is marginally significant and negative when defendants receive non-material court decisions. We also extend the event windows to (-1, 1) and (-2, 2), as reported in Panel B and Panel C of Table 2. The abnormal returns are spanned over a longer window than those of the decision announcement dates. The findings are consistent with the results for the event day (0) abnormal returns.

Investors, especially institutional investors and insiders, have the incentive, motivation, and resources to obtain and process information (Brunnermeier, 2005). Thus, investors might trade on the private information before the court decisions are announced, leading to significant turbulence in stock prices before the decision dates. On the other hand, investors may overreact or underreact to the court decisions (Bondt et al., 1987). As a result, the significant cumulative abnormal returns over the longer event windows can also be a result of investors' irrational trading activities. To disentangle the two types of trades, we test abnormal stock returns for the following two event windows: (-2, -1) and (1, 2). The results are reported in Table 3. As shown in Panel A, before the decisions are announced, the mean CAR is significantly positive with a value of 1.508% for Plaintiffs (Favorable). Whereas, the pre-event average CAR is -1.964% (t-value=-2.55) when the outcomes are unfavorable for plaintiffs. We do not observe significant results for defendants. The findings are not surprising since plaintiff firms are actively seeking resolutions while defendants are holding ground. A more interesting implication of such results is that they are in line with information leaking hypothesis. In order to fully illustrate this point of view, we need to combine the results in both panel A and panel B of Table 3.

Panel B of Table 3 presents the results for post-event abnormal returns. In the cases of Plaintiffs (Favorable), we do not observe significant market reaction after the event day. One explanation is that the information content of the decisions on plaintiffs has been substantially explored by investors and incorporated into stock prices before and on the decision announcement dates. In comparison, the defendant favorable group shows no evidence of significant CAR before the decision announcement dates due to investors holding around. However, the mean CAR is 0.391% and significant for Defendants (Favorable) during the post-event window of (1, 2). Investors do not discriminate against defendant firms when they intend to profit from private information. Information leaking hypothesis solely is far from enough to fully explain the differences in CAR between plaintiff and defendant group, as well as the differences in CAR between pre and post-event windows for both groups. The findings suggest that investors also overreact to good news while they are digging for private information. For both unfavorable decision groups, there is no significant market reaction after the decision dates. The combined results are consistent with Eastwood and Nutt (1999) and Chan (2003), which conclude that investors overreact to good news and underreact to bad news. In summary, the evidence also supports the investors' irrational reaction hypothesis.

Long-term Corporate Decisions

Extensive studies have documented the consequences when firms are charged with misconduct. In addition to the legal penalties that firms are responsible for (Karpoff et al., 2008a; Karpoff et al., 2005), reputational losses are even more substantial (Karpoff et al., 2008b). Similarly, firms will also have to face loss in their future investment and growth opportunities (Karpoff et al., 2013). Essentially, the punishments to firms would be imposed more by the market in the long run.

We next examine the long-term effects of the trade secret lawsuits. We employ a difference-in-difference multivariate regression analysis for a ten-year event window (Event year -5 to Event year -1, and Event year +1 to Event year +5). For each firm in the sample, the industry average of the same event year is constructed as the control group. The variable *Lawsuit* is a dummy variable that takes the value of 1 if a firm is in our sample, and 0 if it is the industry average. *Post* is an indicator with the value of 1 for the post-lawsuit fiscal year and 0 otherwise. The interaction of these two indicators is also introduced to compare the different effects of the lawsuits before and after the decision announcement dates. The description of each variable is summarized in Appendix Table A2. Panel A of Table 4 shows that firms receiving favorable court decisions do not seem to obtain many benefits in the long run, except for higher cash holdings. Nevertheless, with respect to unfavorable outcomes in Panel B of Table 4, the consequences seem to be more long-lasting. Specifically, firms receiving unfavorable court decisions conduct fewer R&D activities, spend less on capital expenditures, lose more intangible assets, and hold less cash. In addition, these firms also become more conservative in weighing debts after the lawsuits. The lower leverage used by firms losing the lawsuits can be due to precautionary reasons because the actual economic outcomes of the loss are uncertain until they eventually realize the loss. It is also likely that the reputation loss gives them less access to debt financing. In addition, these firms continue to have a lower-than-before market-to-book ratio after the lawsuit. In Appendix Table A3, we also compare the industry-adjusted firm fundamentals the year before and after the decision announcement dates. It seems that firms with favorable outcomes improve their fundamentals immediately after the court decisions. In summary, while firms winning the cases seem to benefit from the lawsuits, most of the positive effects are temporary. In comparison, firms with unfavorable court announcements suffer more from the legal events in the longer term. As an extension of prior studies, the results imply that the punishment borne by the market is more substantial for firms losing the litigations.

Conclusion

This paper studies how a firm's involvement in a trade secret lawsuit and the following court decision favorability affect the firm's market valuation and corporate policies. Using 137 trade secret cases with 312 trials, we find that stock prices of firms respond to favorable (unfavorable) court decisions with positive (negative) abnormal returns during a five-day window (-2, 2) relative to the court decision announcement dates. The abnormal returns around the event days are consistent with the investors trading behavior that they dig information leaking and overreact/underreact to good/bad news. We further find that the effects from the trade secret court decisions can be long-lasting, especially for firms losing the cases during the process. Overall, our studies indicate that the market is incline to punish firms that lose the litigations in the long run instead of rewarding winning ones.

Table 1 Summary Statistics

This table reports the descriptive statistics for 213 trade secret cases in which at least one public company is involved. Cases cover the period of 1992 to 2012. Case data is hand collected from LexisNexis database, and companies present in the trials are merged with CRSP and COMPUSTAT database. The whole sample is divided into plaintiffs group and defendants group. Each group contains three subsets based on the court decisions.

All Cases with Public Firms					
Number of Cases			213		
	Mean	Median	Mode	Max	Min
Number of Trials within a Case	4.83	3	2	34	2
Final Sample (Trials with Return Data Available)					
Number of Cases			137		
Number of Trials			312		
Court Decisions			Obs. for Each Decision Group		
Favorable to Plaintiffs			57		
Unfavorable to Plaintiffs			31		
Favorable to Defendants			68		
Unfavorable to Defendants			58		
Non-material Trials from Plaintiffs Group			57		
Non-material Trials from Defendants Group			41		

Table 2 Stock Market Reaction around Decision Dates

This table reports the stock market reaction around the decision dates for the 6 decision groups during the period of 1992 to 2012. The event windows include Event Day (0), (-1, 1), and (-2, 2). The stock market reaction is measured using cumulative raw returns (CRET) and cumulative abnormal returns (CAR) over the event windows. We estimate beta by regressing a firm's daily stock returns on the market returns over the 5-year period ending on the trading day before the event window. The estimated beta is then used to calculate the stock predicted returns during the event windows. We measure abnormal returns as the difference between actual stock returns and the predicted returns. The table presents the number of observations (N), the average of cumulative raw returns (Mean CRET), the average of cumulative abnormal returns (Mean CAR), the median of cumulative abnormal returns (Median CAR), the percentage of positive abnormal returns, and Patell's t value.

Panel A: Event Day (0) Abnormal Returns						
Court Decisions	N	Mean CRET	Mean CAR	Median CAR	% of +AR	Patell's t
Plaintiffs (Favorable)	57	2.021%	2.284%	1.133%	85.96%	4.30
Plaintiffs (Unfavorable)	31	-1.160%	-1.365%	-0.736%	32.26%	-2.13
Defendants (Favorable)	68	2.464%	2.171%	1.166%	82.35%	6.12
Defendants (Unfavorable)	58	-1.618%	-1.739%	-0.917%	17.24%	-3.70
Plaintiffs (Non-material)	57	0.808%	0.627%	-0.142%	40.35%	1.58
Defendants (Non-material)	41	-0.700%	-0.591%	-0.470%	34.15%	-1.73
Panel B: Event Window (-1, 1) Abnormal Returns						
Court Decisions	N	Mean CRET	Mean CAR	Median CAR	% of +AR	Patell's t
Plaintiffs (Favorable)	57	3.500%	3.568%	1.858%	71.93%	4.30
Plaintiffs (Unfavorable)	31	-1.823%	-2.029%	-2.149%	32.26%	-2.27
Defendants (Favorable)	68	3.221%	2.766%	1.517%	75.00%	6.18
Defendants (Unfavorable)	58	-2.475%	-2.675%	-1.090%	31.03%	-3.00
Plaintiffs (Non-material)	57	1.383%	1.096%	-0.144%	49.12%	1.71
Defendants (Non-material)	41	0.131%	-0.361%	-0.848%	26.83%	-1.38
Panel C: Event Window (-2, 2) Abnormal Returns						
Court Decisions	N	Mean CRET	Mean CAR	Median CAR	% of +AR	Patell's t

Plaintiffs (Favorable)	57	4.058%	4.306%	2.489%	68.42%	3.93
Plaintiffs (Unfavorable)	31	-2.455%	-2.477%	-2.716%	32.26%	-1.85
Defendants (Favorable)	68	3.096%	2.872%	1.463%	64.71%	4.53
Defendants (Unfavorable)	58	-1.820%	-1.854%	-1.167%	34.48%	-1.83
Plaintiffs (Non-material)	57	2.110%	1.834%	0.516%	56.14%	2.18
Defendants (Non-material)	41	0.998%	0.306%	0.172%	53.66%	-0.28

Table 3 Pre- and Post- Decision Announcement Dates Abnormal Returns

This table reports the stock market reaction around the decision dates for the 6 decision groups during the period of 1992 to 2012. The event windows include (-2,-1) and (1,2). The stock market reaction is measured using cumulative raw returns (CRET) and cumulative abnormal returns (CAR) over the event windows. We estimate beta by regressing a firm's daily stock returns on the market returns over the 5-year period ending on the trading day before the event window. The estimated beta is then used to calculate the stock predicted returns during the event window. We measure abnormal returns as the difference between actual stock returns and the predicted returns. The table presents the number of observations (N), the average of cumulative raw returns (Mean CRET), the average of cumulative abnormal returns (Mean CAR), the median of cumulative abnormal returns (Median CAR), the percentage of positive abnormal returns, and Patell's t value.

Panel A: Event Window (-2, -1) Abnormal Returns						
Court Decisions	N	Mean CRET	Mean CAR	Median CAR	% of +AR	Patell's t
Plaintiffs (Favorable)	57	1.310%	1.508%	0.971%	63.16%	2.38
Plaintiffs (Unfavorable)	31	-1.982%	-1.964%	-1.515%	16.13%	-2.55
Defendants (Favorable)	68	0.205%	0.304%	0.126%	57.35%	0.40
Defendants (Unfavorable)	58	0.160%	-0.045%	-0.276%	41.38%	-0.11
Plaintiffs (Non-material)	57	1.031%	0.797%	-0.018%	49.12%	1.95
Defendants (Non-material)	41	0.270%	0.040%	-0.378%	39.02%	-0.38
Panel B: Event Window (1, 2) Abnormal Returns						
Court Decisions	N	Mean CRET	Mean CAR	Median CAR	% of +AR	Patell's t
Plaintiffs (Favorable)	57	0.536%	0.486%	0.284%	56.14%	0.75
Plaintiffs (Unfavorable)	31	0.657%	0.899%	0.215%	51.61%	1.17
Defendants (Favorable)	68	0.456%	0.391%	-0.041%	48.53%	2.41
Defendants (Unfavorable)	58	-0.334%	-0.067%	-0.455%	43.10%	-0.16
Plaintiffs (Non-material)	57	0.369%	0.398%	-0.078%	49.12%	0.37
Defendants (Non-material)	41	1.450%	0.853%	0.732%	58.54%	1.16

Table 4 Difference-in-Difference Regression Analysis

This table reports the difference-in-difference regression analysis for a ten-year event window (Event year -5 to Event year -1, and Event year +1 to Event year +5). For each firm in the sample, the industry average of the same event year is constructed and included as a control group. The variable Lawsuit is a dummy variable that takes the value 1 if a firm is in our sample, and 0 if it is the industry average. Post is an indicator with the value 1 for the post-lawsuit fiscal year and 0 otherwise. The definitions of all other variables are described in Appendix Table A2. We control for the year and industry fixed effects. t-values are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Panel A: Favorable Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	R&D	CAPEX	Intangible	Q	Cash	Debt
Lawsuit	-0.123***	-0.068***	-0.091***	-20.728***	-0.368***	0.009
	(-6.91)	(-6.15)	(-2.88)	(-7.10)	(-7.97)	(1.08)
Post	-0.021	-0.01	-0.039	-7.587**	-0.142**	0.011
	(-0.91)	(-0.71)	(-0.96)	(-1.99)	(-2.32)	(1.04)
Lawsuit*Post	0.026	0.007	0.031	2.928	0.158**	0.002
	(1.02)	(0.42)	(0.69)	(0.71)	(2.42)	(0.18)
Obs.	867	1,141	1,170	1,151	1,205	1,447
R-squared	0.131	0.119	0.039	0.11	0.111	0.023

Panel B: Unfavorable Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	R&D	CAPEX	Intangible	Q	Cash	Debt
Lawsuit	-0.097***	-0.041*	-0.063	-12.244***	-0.358***	-0.181**
	(-3.49)	(-1.78)	(-1.11)	(-3.42)	(-4.11)	(-2.55)
Post	0.109***	0.157***	0.178**	5.282	0.136	0.204**
	(3.16)	(5.09)	(2.36)	(1.12)	(1.15)	(2.13)
Lawsuit*Post	-0.131***	-0.108***	-0.221***	-18.750***	-0.204*	-0.175*
	(-3.49)	(-3.35)	(-2.81)	(-3.78)	(-1.68)	(-1.77)
Obs.	726	894	901	885	945	947
R-squared	0.161	0.15	0.102	0.158	0.115	0.067

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Appendix (Essay 1)

Centrality

This table adds one additional control variable to Table IX: eigenvector centrality of the supplier firms in the customer-supplier network. Eigenvector centrality is the first eigenvector of the customer-supplier network's adjacency matrix. We form the customer-supplier network matrix using sales number. Customer factor is monthly aggregated idiosyncratic returns of all customers in our sample. Idiosyncratic returns are the residuals backed out from a firm's monthly excess return using a model controlling for Fama and French 3 factors (MKTRF, SMB, and HML) in addition to its corresponding value weighted industry mean returns. Peripheral customers are customer firms with less than 3 suppliers in our sample. Size is a firm's market capitalization in the previous month. BM is calculated as current fiscal year's book equity to the firm's market equity in June. All stock returns are matched with BM from previous fiscal year. The regressions also controls for lag monthly (lag(RET)) and annual returns (Lag(RET_1Year)). The regressions follow Fama-Macbeth methodology. Betas of each independent variable are first estimated using the 36-month rolling window in the first step. The second step runs cross-sectional regression of supplier returns on each as well as all betas in the months immediately following the rolling windows. The sample includes common stocks listed at NYSE, NASDAQ, and AMEX. Utility firms, financial institutions, microcap stocks (stock prices lower than $5), and ADRs are excluded.

Customer Factor	0.0563***			0.0515***
	(3.02)			(2.70)
Peripheral Customers Idiosyncratic Returns		0.0893		0.0690
		(1.65)		(1.32)
Market Idiosyncratic Returns			0.0117	0.0215
			(0.51)	(0.95)
Centrality	2.780	2.330	2.500	2.380
	(1.31)	(1.12)	(1.18)	(1.16)
MKTRF	-0.0707	-0.0968	-0.0880	-0.109
	(-0.46)	(-0.62)	(-0.58)	(-0.73)
Log(Size)	-0.0719*	-0.0931**	-0.0645*	-0.0958***
	(-1.92)	(-2.58)	(-1.71)	(-2.67)
BM	0.335*	0.161***	0.335*	0.144**
	(1.75)	(2.60)	(1.81)	(2.39)
Lag(RET)	-4.100***	-4.190***	-4.210***	-4.430***
	(-7.04)	(-7.14)	(-7.24)	(-7.41)
Lag(RET_1Year)	0.355*	0.282	0.355*	0.319*
	(1.76)	(1.48)	(1.81)	(1.72)
Constant	0.941**	1.200***	0.880**	1.240***
	(2.30)	(3.25)	(2.12)	(3.46)
Number of Obs.	143980	143980	143980	143980
Adjusted R^2	0.085	0.085	0.085	0.099

Appendix (Essay 2) Table A1 Summary Statistics for Non-material Trials

This table reports the descriptive statistics for non-material trials. Case data is hand collected from LexisNexis database. Court decisions are categorized into three categories for both plaintiffs and defendants groups: favorable, unfavorable, and non-material. Cases cover the period of 1992 to 2012. Reasons and the number of non-material trials are presented.

Reasons for Non-Material Decisions	Obs
Motion to seal opinions	3
Appeal court affirmed previous decisions	11
Motive to gain access to sealed documents	5
Bankruptcy cases	8
Neutral statements	33
Fought over legal expenses less than $100,000	6
Court requested for more information	14
Motions were brought up by non-party	4
Motion to consolidate	4
Motion to compel arbitration	10
Total	98

Appendix (Essay 2) Table A2 Variable Definitions

Variable	Definition	Data Source
R&D	XRD/AT	Compustat
Capital	CAPX/AT	Compustat
Debt	(DLTT+DLC)/AT	Compustat
Intangible	INTAN/AT	Compustat
Cash	CH/AT	Compustat
Q	(AT+PRCC_F*CSHO-CEQ)/AT	Compustat

Appendix (Essay 2) Table A3 Short-term Difference in Firm Characteristics between Sample and Industry

This table reports the univariate results of a firm's industry-adjusted fundamentals the fiscal year before and after the lawsuit court decision announcement dates. The industry that a firm belongs to is identified using the four-digit SIC code. The definitions of all the variables are described in Appendix Table A2. We calculate a firm's industry-adjusted fundamentals by comparing a firm's fundamentals with firms within the same industry during the same fiscal year. We then take the average of each variable across the sample. For each variable, t-values are reported for both pre- and post- announcement groups. Besides, t-values for the difference between the pre- and post-event windows are also reported. Panel A and Panel B report the univariate results for firms with favorable court decisions and unfavorable court decisions, respectively.

Panel A: Firms with Favorable Outcomes						
Variables	Observation Year	Mean	Median	Std	t-value	t-value (Post-Pre)
R&D	Pre-announcement	-0.1317	-0.0038	0.4765	-11.52	3.89
	Post-announcement	-0.0750	0.0000	0.3607	-8.35	
CAPEX	Pre-announcement	-0.0534	0.0120	0.3132	-10.03	4.89
	Post-announcement	-0.0212	0.0033	0.1544	-7.10	
Debt	Pre-announcement	-0.1737	0.0000	0.7409	-12.00	4.56
	Post-announcement	-0.0863	0.0000	0.6211	-6.93	

Intangible	Pre-announcement	-0.0451	0.0022	0.5439	-4.49	4.19
	Post-announcement	0.0123	0.0086	0.4009	1.45	
Cash	Pre-announcement	-0.3742	-0.0179	1.5926	-14.15	3.89
	Post-announcement	-0.2504	-0.0326	0.9529	-14.12	
Q	Pre-announcement	-8.8685	0.1920	51.8485	-9.61	1.01
	Post-announcement	-7.5636	0.2956	44.8469	-8.36	

Panel B: Firms with Unfavorable Outcomes

Variables	Observation Year	Mean	Median	Std	t-value	t-value (Post-Pre)
R&D	Pre-announcement	-0.1410	-0.0067	0.5504	-11.90	0.09
	Post-announcement	-0.1394	0.0079	0.6238	-10.62	
CAPEX	Pre-announcement	-0.0427	-0.0044	0.2892	-8.33	-5.09
	Post-announcement	-0.0802	-0.0096	0.3018	-15.11	
Debt	Pre-announcement	-0.1256	0.0000	0.6414	-9.68	0.23
	Post-announcement	-0.1212	0.0000	0.7160	-9.04	
Intangible	Pre-announcement	-0.0103	0.0000	0.7897	-0.70	-7.08
	Post-announcement	-0.1630	0.0000	0.8656	-10.47	
Cash	Pre-announcement	-0.3972	-0.0290	1.8552	-12.18	-3.56
	Post-announcement	-0.6000	-0.0073	2.6891	-13.09	
Q	Pre-announcement	-5.8670	-0.2823	34.9396	-9.06	-4.31
	Post-announcement	-10.8198	0.1117	51.9118	-11.59	

Curriculum Vitae

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Selected Abstracts

“Aggregation of Idiosyncratic Shocks in Customer-Supplier Network”

I investigate the channels of information diffusion along the supply chain after documenting strong contemporaneous return comovement between customer and supplier firms. Using Cen, Da, and Zhao’s (CDZ, 2013) methodology, I decompose customer’s returns into cash flow and discount rate components. The evidence suggests information transmit through both channels. Nevertheless, the establishment and revelation of the economic links induce additional cash flow news passage, and the aggregated cash flow news drives the comovement higher. Further examinations reveal the cash flow channel tunnels firm-specific information including earnings, and the trade credits influences flow through discount rate channel. The study contributes to both financial information channels research and stock return comovement literature. Revealing information channels carries critical messages and implications to not only professional investors, but also the whole market.

“Economic Outcomes of Corporate Espionage”

This study investigates financial outcomes of trade secret lawsuits through stock market reactions to court decisions, using hand-collected case data from LexisNexis database. We depict the big pictures of the legislative process and examine possible explanations for the abnormal returns from information leak and overreaction/underreaction perspectives. The firm-level difference-in-differences study suggests the lawsuit outcomes both encourage R&D investment and disturb firm’s capital expenditure, communicating implications for corporations' employment and investment policies.

“Investing Precautionary Cash Reserve”

This paper investigates how quickly and effectively corporations invest the cash raised from equity and debt financing for precautionary purposes. Using a cash half-life measure, we find it takes firms about 4 to 6 years to invest the cash reserve. Precautionary cash reserve raised from both equity and debt financing is used to fund capital expenditure and retire existing liabilities. The evidence reveals the rationale and effectiveness of manager’s decision to raise precautionary cash reserve. Precautionary cash is raised when the market interest rate is lower, or when managers foresee future investment opportunities.