Speed Matters: Limited Attention and Supply-Chain Information Diffusion*

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Abstract:

Using the methodology of Hou and Moskowitz (2005), we develop a new measure of the speed of information diffusion along the supply chain. Using this measure, we find evidence that information diffuses more quickly when key market participants are less subject to limited attention constraints. Specifically, we find that the speed of information diffusion from customer to supplier stock returns is more rapid when analysts dual-cover, brokerage firms dual-cover, and institutional investors cross-invest in the supplier and its principal customer. We rely on exogenous shocks to attention from regional flu epidemics to establish causality. We demonstrate that our speed measure is useful in identifying customer momentum strategies and can be of value to managers who use information in stock prices to guide corporate decisions.

Key Words: Supply Chains; Speed; Information Diffusion

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1. Introduction

Previous studies show that close customer-supplier relationships are an important channel of information diffusion in financial markets. For example, information related to bankruptcy and financial distress (Hertzel, Li, Officer, and Rodgers, 2008), idiosyncratic shocks (Barrot and Sauvagnat, 2016), mergers and acquisitions (Fee and Thomas, 2004), technology innovations (Chu, Tian, and Wang, 2017; Dasgupta, Zhang, and Zhu, 2015), and tax strategies (Cen, Maydew, Zhang, and Zuo, 2016) diffuses along the supply chain. In addition, recent studies suggest that market participants' attention to supply-chain relationships, such as analyst dual-coverage (Guan, Wong, and Zhang, 2015), institutional cross-holding (Cohen and Frazzini, 2008; Cen, Danesh, Ornthanalai, and Zhao, 2015), and online co-search of customers and suppliers (Agarwal, Leung, Konana, and Kumar, 2017) facilitates supply-chain information diffusion.

Both investors and managers can benefit from a better understanding of information diffusion through supply-chain channels. Cohen and Frazzini (2008) show that stock returns of principal customers predict stock returns of their dependent suppliers when investors underreact to supply-chain-specific information.[1] Therefore, sophisticated investors, such as hedge fund managers, can benefit from trading strategies based on supply-chain information diffusion. From the firm's perspective, Chen, Goldstein, and Jiang (2007) suggest that stock prices can act as information sources that guide corporate managerial decisions. In a supply-chain context, Williams and Xiao (2016) show that managers of supplier firms use customer stock prices to guide their

[1] The Cohen-Frazzini customer momentum trading strategy involves buying supplier firms whose customers had the most positive returns (highest quintile) in the previous month and short-selling firms whose customers had the most negative returns (lowest quintile). Cohen and Frazzini (2008) show that this strategy generates abnormal returns of 1.55% per month, or an annualized return of 18.6% per year.

corporate decisions. For these managers, understanding the extent to which customer-related information is already reflected in their stock prices can be of value.

Practitioners and researchers face two major challenges in exploring and understanding supply-chain information diffusion. First, for practitioners, the profitability of customer momentum investment strategies as well as the success of corporate decisions based on price feedback effects critically depends on the ability to accurately measure and incorporate the speed of supply-chain information diffusion in their decision-making. However, there exist no verified measures for the speed of supply-chain information diffusion that can guide investors and corporate managers. Second, researchers face serious endogeneity concerns when studying determinants of the speed of supply-chain information diffusion. For example, it is difficult to establish a causal relationship between the speed of information diffusion and market participants' attention to supply-chain relationships given that they are likely driven by common, but unobservable, economic forces. We address both challenges in this paper.

Using the methodology of Hou and Moskowitz (2005), we first compute a delay measure of the speed of supply-chain information diffusion based on the degree to which supplier returns reflect past customer returns. We calculate this measure using customer and supplier stock returns in the period surrounding earnings announcements of customer firms. This setting allows us to measure information diffusion around an important information event through supply-chain economic links and, therefore, largely mitigates the information environment concerns with measures of price delay raised in Griffin, Kelly, and Nardari (2010). Consistent with earlier evidence on the role of attention in facilitating supply-chain information diffusion (e.g., Agarwal, Leung, Konana, and Kumar, 2017), our initial tests find that the speed of supply-chain information diffusion is positively correlated with key market participants' attention to supply-chain relationships, as proxied by analyst dual-coverage, broker dual-coverage, and institutional cross-holding of both the customers and suppliers. We show that these correlations are statistically significant, economically meaningful, and robust to controls for a host of firm and relationship characteristics.

To establish a causal relationship between the speed of information diffusion and attention to supply-chain relationships, we rely on an exogenous shock that affects the attention of key market participants: regional flu epidemics in the U.S. Following Dong and Heo (2014), our tests are based on the intuition that a flu infection, with common symptoms such as fever and fatigue lasting for one to two weeks, may lead to a reduction in attention and information processing capabilities of analysts and institutional investors. In addition to the analysts and institutional investors themselves, flu that affects their family members, colleagues, and/or support staff may also slow information diffusion, even if the institutional investors and analysts themselves are not directly affected.

From the Center for Disease Control (CDC) we obtain two measures of local flu epidemics in the U.S., the 'percentage of flu tests with positive results' and the 'percentage of patient visits to healthcare-provider for flu-like symptoms', both by broad geographic region. We identify local peaks of flu exposure as those weeks when the flu measures are simultaneously higher than the historical average for the region and the average concurrent flu measures in all other U.S. regions. Our first set of tests focuses on flu exposure in the New York Region, the workplace and residence of most financial analysts. In a triple-difference specification, we show that supply-chain information diffuses more slowly when the New York area is affected by a serious flu epidemic. More importantly, consistent with the role of analyst and broker dual-coverage in facilitating supply-chain information diffusion, we find that this effect is much stronger when the affected analysts and brokers cover both customers and suppliers. Using data on the headquarter locations of institutional investors, we find similar results for institutional cross-holding of customers and suppliers, i.e., the speed of information diffusion along supply chains declines when financial institutions that cross-hold both customers and suppliers are located in areas that are affected by a flu epidemic. Taken together, these findings provide novel and causal evidence that attention to supply-chain relationships increases the speed of information diffusion and verifies that our speed measure captures the effects of limited attention identified in earlier literature.

We next investigate the potential usefulness to practitioners of our measure of the speed of supply-chain information diffusion. With respect to investors, we test whether our measure can generate a "sharper", more profitable Cohen-Frazzini customer momentum strategy by identifying relationship-pairs where information diffuses more slowly from customers to suppliers. Within the slow information diffusion group, the Cohen-Frazzini customer momentum strategy generates an average hedging portfolio return of 1.2% per month (significant at the 1% level).[2] This finding stands in sharp contrast to an insignificant 0.2% per month hedging portfolio return for customer-supplier pairs in the fast information diffusion group. We also find that our speed measure does better at identifying profitable customer momentum strategies than firm size, which is also a continuous measure, but only a "proxy" for diffusion speed. Specifically, the hedging portfolio return in our slow diffusion group is 23.8% higher than the hedging portfolio return for relationship-pairs sorted by market capitalization.[3] Our results are robust to inclusion of the market

[2] The magnitude of hedging portfolio returns based on the customer momentum strategy in our sample period is smaller than that reported in Cohen and Frazzini (2008). This result is consistent with McLean and Pontiff (2016) that academic publications weaken stock return predictability.
[3] We also find that in the high-speed group, the hedging portfolio return is significantly lower than that in the large size group.

factor, the Fama-French (1993) size and value factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

We also examine the extent to which the speed of information diffusion along the supply chain can affect the ability of managers to learn from their own stock prices and the stock prices of closely related firms. We show that as the speed of information diffusion from customers to suppliers becomes slower, suppliers' investment sensitivity to their own stock prices decreases whereas suppliers' investment sensitivity to their customer's stock prices increases. This finding is consistent with the idea that the speed of supply-chain information diffusion alters the balance with which Tobin's *Qs* of customers and suppliers reflect fundamental information for the suppliers and, thus, provides another verification of our speed measure. Furthermore, this result is also consistent with slow information diffusion causing suppliers to rely less on their own stock prices versus their customers' stock prices as information sources when making investment decisions.

In addition to the supply-chain literature, our paper also contributes to a broader literature on behavioral finance and market efficiency. The speed of information diffusion has been a central issue for the efficient markets hypothesis, which holds that all relevant public information is reflected in asset prices instantaneously. Although a large body of research has highlighted the importance of firm and industry characteristics for the speed at which markets incorporate new information (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Hou, 2007), few studies have investigated information diffusion speed in an economic setting where the type of information diffusion is identifiable. We contribute to this literature by being the first study to show that analyst dual-coverage, broker dual-coverage, and institutional cross-holding of customers and suppliers have a causal impact on the speed of information diffusion along supply chains.

The rest of this paper is organized as follows. Section 2 summarizes our data sources and presents summary statistics for our sample. In Section 3, we outline our empirical approach for measuring the speed of information diffusion along supply chains around customers' earnings announcements and show that our speed measures are positively correlated with analyst dual-coverage, broker dual-coverage, and institutional cross-holding. In Section 4, we discuss our identification strategy based on flu epidemics and provide evidence that the attention of dual-covering analysts and brokers, and cross-holding institutional investors has a causal effect on the speed of supply-chain information diffusion. We present results of tests of the effect of our speed measure on customer momentum investment strategies as well as its effect on suppliers' investment sensitivities to their own and their customers' Tobin's *Q*s in Section 5. Section 6 concludes.

2. Data and Descriptive Statistics

2.1. Customer-Supplier Relationships

Regulation S-K requires all public firms in the U.S. to disclose the existence and the names of customers representing more than 10% of their total sales.[4] In practice, a firm can also voluntarily disclose customers that account for less than 10% of total revenues. We define a firm as a *principal customer* in year *t*, if it has been reported as a customer by at least one Compustat firm in year *t*. Similarly, a firm is defined as a *dependent supplier* in year *t* if it has disclosed at least one principal customer in that year. Accordingly, the *customer-supplier relationships* defined in this paper are relationships between principal customers and their dependent suppliers. Relying

[4] SFAS 14 (before 1997) and SFAS 131 (after 1997) also require U.S. firms to disclose the existence of major customers representing more than 10% of their total sales.

on the Compustat Segment Customer File, we follow the approach used in Banerjee, Dasgupta, and Kim (2008) and Cohen and Frazzini (2008), and manually match corporate customer names with their Compustat identifiers (i.e., GVKEYs) whenever possible. To obtain a measure of the importance of the *principal customer* to the *dependent supplier* we divide the annual sales to the *principal customer* reported in the Compustat Segment Files by the total annual sales of the supplier in the given year (i.e., *Pct of Supplier Sales*). We further obtain quarterly earnings announcement dates as well as standard firm characteristics such as book value of total assets, total sales, market capitalization, cost of goods sold, and other items from the Compustat Annual and Quarterly Files.

To calculate our measures for the speed of information diffusion around customer firms' earnings announcements, we require daily stock returns for both customers and suppliers. We exclude relationship-quarters which do not have at least 25 daily return observations in the [-10, 30] interval around the customer's earnings announcement date. We also require that all firms in our sample have available information on security characteristics, including stock prices and returns from CRSP.

Data on quarterly earnings announcements including the actual earnings per share, mean and median earnings forecasts, forecast dispersion, and analyst coverage for both customers and suppliers are obtained for the 1983 to 2013 sample period from the I/B/E/S Summary History File. In most of our tests, our variables from I/B/E/S reflect the most recent forecast of each analyst before the earnings announcement date.

Our sample selection criteria above yield a final sample of 14,715 customer-supplier pairs (5,540 unique suppliers and 2,283 unique customers) from 1983 to 2013, providing a total of 141,488 observations, where the unit of observation is a relationship-quarter. Detailed definitions of all variables used in our study are provided in Appendix I. We winsorize all accounting related variables at the 1% level to minimize the effect of outliers that are likely driven by reporting errors.

[Insert Table 1 Here]

Summary statistics describing customer firms, supplier firms, and customer-supplier relationships are presented in Panel A of Table 1. Consistent with Banerjee, Dasgupta, and Kim (2008), among others, principal customer firms in our sample are typically much larger than their dependent suppliers. The average customer firm is about 50 times larger than the average supplier firm in terms of the book value of total assets and about 40 times larger in terms of market capitalization. Not surprisingly, we also note that principal customers have higher analyst coverage with a median of 23 analysts compared to a median of only three analysts for dependent supplier firms. The ratio of sales to the principal customer over total sales reported by suppliers (*Pct of Supplier Sales*) is around 19.5%, on average, with an interquartile range of 10.6% to 23.0%. Although a principal customer is important to a supplier, the reverse is not typically case. In our sample, suppliers only contribute a small fraction of their customers' total inputs; supplier sales to customers on average represent only 1.4% of the customers' cost of goods sold (COGS).[5]

2.2. Analyst Dual-Coverage, Brokerage Dual-Coverage, and Institutional Cross-Holding

We rely on the I/B/E/S Detail History File to obtain annual measures of analyst dual-coverage and broker dual-coverage. For every relationship-year in our sample from 1983 to 2013 we calculate the number of analysts as well as the number of brokerage firms that have issued a quarterly or annual forecast for the customer firm and the supplier firm. We define *analyst dual-coverage* for a relationship-year, if an analyst simultaneously covers both the customer and the

[5] We note that suppliers that have unique products and make relationship-specific investment tend to be important to their customer firms even if the percentage of their inputs in the customer's total cost of goods sold is small.

supplier.[6] We similarly define *brokerage dual-coverage* if analysts from a brokerage firm simultaneously cover both the customer and the supplier. For our main test specification, based on relationship-quarter observations, we assume that the analyst dual-coverage and brokerage dual-coverage status does not change within a calendar year.[7]

From the Thomson Reuters Institutional Investors (13f) database we obtain information for institutional cross-holding for each relationship-quarter. Institutional cross-holding in a relationship-quarter is recorded if at least one institutional investor owns more than 1% of the outstanding shares of both the supplier and the customer firm during the respective quarter. We also use the FactSet LionShares Ownership File to obtain the location of the institutional investor (i.e., city and state) and to classify the institutional investor as either active or passive. Since cross-holding of passive institutional investors is primarily driven by mechanical effects, such as the coexistence of the customer and supplier in common stock indices, we only consider cross-holding by active institutional investors. The information related to the locations of the cross-holding institutional investors is particularly important for our tests that rely on flu epidemics (i.e., reported in Section 4.2), since the flu is a local phenomenon and affects market participants differently depending on their locations.[8]

As shown in Panel A of Table 1, 24.8% of the relationship-quarters in our sample are analyst dual-covered by at least one analyst that simultaneously covers both the customer and the supplier firm. 54.5% of relationship-quarters are broker dual-covered and 25.6% of relationship-

[6] An analyst is defined as covering a firm in a given year if the analyst makes at least one earnings forecast for that firm in that year.
[7] When analysts do not make frequent updates, defining analyst dual coverage and brokerage dual coverage based on updates of analyst forecasts in a quarterly frequency would lead to a noisy measure.
[8] Our current set of tests on analyst and broker dual-coverage currently focus on flu in the New York region. We are currently collecting data on analyst locations in order to expand those tests.

quarters have customer-supplier pairs cross-held by at least one common active institutional investor. On average, each relationship-quarter is covered by 0.75 dual-covering analysts, 2.93 dual-covering brokerage firms, and 0.74 cross-holding institutional investors.

3. Speed of Information Diffusion around Earnings Announcements

3.1. Speed Measures

To estimate the speed of supply-chain information diffusion we focus on quarterly earnings announcements which are important, recurring, and firm-specific information events. Pandit, Wasley, and Zach (2011) show that suppliers experience large abnormal stock returns when their principal customers disclose earnings shocks and that the magnitude of the supplier reaction depends on the strength of the customer-supplier relationship. In this setting, we observe sufficient variation in stock returns driven by the arrival of new firm-specific information. Further, around earnings announcements, price movements are more likely dominated by the diffusion of earnings information instead of macroeconomic or industry-specific components. This setting offers a comparable environment of information production across firms, which largely mitigates concerns raised in Griffin, Kelly, and Nardari (2010). As a result, this setting allows us to obtain a more efficient and less noisy estimate of the diffusion of firm-specific information along the supply chain.

Summary statistics on earnings announcement effects are presented in Panel B of Table 1. The standardized earnings surprise (*SUE*) for a customer firm is defined as the difference between actual announced earnings and the latest consensus forecast before the earnings announcement, scaled by the stock price of the customer firm. In our sample, the standard deviation of the absolute value of earnings surprises (*abs(SUE)*) is more than two times larger than its mean value, suggesting a large dispersion of earnings surprises (in absolute magnitude). This confirms that earnings announcements are major disclosure events of firm-specific information that significantly affect stock returns. Further, consistent with previous studies (e.g. Matsumoto, 2002; Bartov, Givoli, and Hayn, 2002), there are more positive earnings surprises (67.2%) than negative earnings surprises (32.8%) in our sample.

To measure the speed of supply-chain information diffusion we follow the methodology first introduced by Hou and Moskowitz (2005) and recently applied, for example, by Boehmer and Wu (2013) and Bae, Ozoguz, Tan, and Wirjanto (2012) in estimating the delay in the diffusion of information contained in market returns.[9] Specifically, around each customer earnings announcement i, we estimate the following regression using customer and supplier returns over 41-day trading period [-10, 30], i.e., from 10 trading days before to 30 trading days after the earnings announcement date.[10] Our estimation equation is:

$$R_{i,t}^{sup} = \alpha_i + \sum_{k=0}^{K} \beta_{i,k} * R_{i,t-k}^{cus} + \varepsilon_{i,t} \tag{1}$$

where $R_{\mathrm{t}}^{\mathrm{sup}}$ denotes daily returns of suppliers; R_t^{cus} denotes daily returns of customers; and K denotes the number of lagged daily returns of customers that we incorporate into our estimation. Intuitively, if information diffusion from customers to suppliers is rapid, i.e., all customer earnings information is incorporated into supplier stock prices within one day, we expect our estimate of β_0 will be positive and significantly different from zero while our estimates of β_k $(k = 1, 2, .. K)$

[9] Hou and Moskowitz (2005) rely on weekly returns over the course of one year. We follow Boehmer and Wu (2013) who consider daily return data over a four-week period.
[10] This time-window is chosen to account for information diffusion during both the pre-earnings and post-earnings announcement periods.

will not be individually or jointly significantly different from zero. Alternatively, if information diffuses slowly from customers to suppliers, some β_k $(k = 1, 2 \ldots K)$ coefficient estimates and/or the sum of these coefficients will be positive and significantly different from zero.

The speed of information diffusion around a customer's earnings announcements is then defined as the ratio of the R^2 of regression Equation (1) when we restrict the coefficients of lags one to four to zero ($\beta_k = 0, \forall k \in [1,4]$), divided by the R^2 of the full model with four lags[11]:

$$S_{04} = \frac{R^2_{\beta_k=0,\forall k\in[1,4]}}{R^2} \tag{2}$$

The larger S_{04}, the smaller the variation in supplier returns that is explained by the lagged customer returns and hence the higher the speed of information diffusion from customers to suppliers. For example, when all customer earnings information is reflected in the supplier's stock price on the customer's earnings announcement day, S_{04} should be equal to 1. Conversely, S_{04} will be smaller when a higher proportion of the variation in the supplier's stock returns is explained by the lagged customer returns, suggesting that information diffuses slowly from customers to suppliers. As reported in Panel C of Table 1, the mean (median) level of S_{04} is 0.256 (.0167) with a standard deviation of 0.256.

Our speed measure, S_{04}, has an economically intuitive interpretation. For example, its mean level suggests that, on average, 25.6% of all information diffusion from customers to suppliers over a one-week horizon is completed within the first day. Although it has the advantage of ease of interpretation, using S_{04} to measure speed of diffusion has two potential limitations.

[11] Although information diffusion may exceed one week, we choose a maximum of four lags (i.e. one week) to strike a balance between having a sufficiently long time-series for estimation purposes and having enough lags to capture meaningful variation in the speed of information diffusion.

First, the distribution of S_{04} is positively skewed (Skewness=0.943), which may violate the normality and linearity assumptions necessary for standard OLS estimation. S_{04} is also bounded within the interval [0,1]. To address these concerns, we follow the literature on price informativeness (e.g. Morck, Yeung, and Yu, 2000) and use a log-transformation of S_{04}, i.e., $logS_{04} = \log\left(\frac{S_{04}}{1-S_{04}}\right)$, as an alternative to S_{04}, which we henceforth refer to as the "unadjusted speed measure". While it is harder to interpret the economic magnitude of the "log-transformed speed measure", this mapping provides a continuous variable ranging from negative to positive infinity, with a distribution closer to normality.

Second, although we compute S_{04} around customers' earnings announcements, it is possible that this measure (as well as its log-transformation) captures the diffusion of important market-wide information in addition to the firm-specific information that we are focused on. To address this concern, we purge the market component by using the residuals from market model regressions for both customers and suppliers. We repeat our computations in equations (1) and (2) based on these return residuals (instead of raw returns) and construct our third speed measure, the "market-adjusted speed measure". Summary statistics in Panel C of Table 1 suggest that the mean of the speed measure based on residual returns is smaller than the mean of the unadjusted speed measure. This is consistent with the notion that firm-specific information, on average, diffuses more slowly than market-wide information. Overall, all three speed measures are highly correlated. Since each speed measure has its own strengths and weaknesses, we apply all three measures in our main tests related to analyst dual-coverage, broker-dual coverage, and institutional cross-holding.

3.2. Determinants of the Speed of Information Diffusion

Previous studies (e.g., Agarwal et al., 2013) have documented that supply-chain information diffusion is facilitated by market participants who pay simultaneous attention to both customers and suppliers. In this section, we carry out a verification test by investigating whether our speed measures indeed exhibit this key observation from earlier literature. Specifically, we examine whether the existence of market participants that focus simultaneous attention on both customers and suppliers – dual-covering analysts, dual-covering brokers, and cross-holding institutional investors – is positively correlated with the speed of information diffusion along supply chains. As noted earlier, we are not able to establish causality in these tests since dual-covering analysts, dual-covering brokers, and cross-holding institutional investors could be endogenously determined.

Our tests are based on estimates of the following panel regression at the relationship-quarter level,

$$Speed_{ijt} = \alpha + X'_{ijt}\beta + Z'_{it}\delta_1 + Z'_{jt}\delta_2 + R'_{ijt}\delta_3 + E'_{it}\delta_4 + \gamma_{ij} + \theta_t + \epsilon_{ijt} \qquad (3)$$

where $Speed_{ijt}$ is one of our speed measures that capture information diffusion from customer i to supplier j in quarter t; Z_{it} and Z_{jt} are vectors of customer and supplier firm-level controls, including firm size and the numbers of analysts covering customers and suppliers. R_{ijt} is a vector of relationship-level controls, including the percentage of total supplier sales that are made to the principal customers, and the percentage of the customer's cost of goods sold that are due to supplier sales to the customer; E'_{it} is a vector of controls for characteristics of customer earnings announcements, including the absolute magnitude and the direction of earnings surprises as well as the pre-earnings-announcement analyst forecast dispersion; γ_{ij} and θ_t represent relationship and time fixed effects, respectively; and X_{ijt} is our main variable of interest representing analyst dual-coverage, broker dual-coverage, or institutional cross-holding. Further, as shown in Figure 1, flu incidence is to some extent a seasonal phenomenon. Peak flu episodes occur more frequently between January and March than in the other months. Therefore, we include quarter fixed effects to control for seasonal patterns in flu incidence as well as other quarter-specific features such as year-end and Christmas effects in our test specifications.

[Insert Table 2 Here]

We first use the unadjusted speed measure as the dependant variable in Equation (3) and report results in Panel A of Table 2. Our results show a positive and statistically significant effect of analyst dual-coverage, broker dual-coverage, and institutional cross-holding on the speed of supply-chain information diffusion. The coefficient of *Analyst Dual Cov* in Column (1) suggests that a one standard deviation increase in analyst dual-coverage (i.e., the number of analysts covering both the customer and the supplier) is associated with an increase of 0.0095 (=0.00531×1.795) in the unadjusted speed measure, which is equivalent to a 3.72% increase based on the unconditional sample average of 0.256. Not surprisingly, the coefficient of *Broker Dual Cov* in Column (2) suggests that the effect of one additional dual-covering broker on the speed of supply-chain information diffusion is weaker than that generated by one additional dual-covering analyst. Further, our results in Column (3) indicate that the economic effect of one additional cross-holding institutional investor is quite comparable to that generated by one additional cross-covering analyst.

We also examine whether analyst dual-coverage, broker dual-coverage, and institutional cross-holding contain incremental information in explaining the speed of supply-chain information. This investigation is motivated by the fact that analyst dual-coverage and broker-dual coverage are mechanically related, i.e., if a customer and a supplier share a dual-covering analyst, they must have a dual-covering broker. In addition, analyst dual-coverage and institutional cross-holding are also economically linked since the assignment of analyst coverage is partially determined by the demand from their buy-side clients, which are mainly institutional investors. To test for incremental explanatory power, we incorporate both broker dual-coverage and institutional cross-holding in the test specification reported in Column (4), and include both analyst dual-coverage and institutional cross-holding in the test specification reported in Column (5). The tests show that the coefficients of both variables remain statistically significant. Overall, our results support the view that analyst dual-coverage (broker dual-coverage) and institutional cross-holding contain incremental information in explaining the speed of supply-chain information diffusion.

To check for robustness, we repeat the same set of tests using the log-transformed and the market-adjusted speed measures as alternative dependent variables in Equation (3). The results, reported in Panels B and C of Table 2, are qualitatively similar to those report in Panel A for the unadjusted speed measure and confirm that market participants with simultaneous attention to both customers and suppliers play an important role in firm-specific information diffusion along supply chains. Furthermore, the results in Panel C, based on the market-adjusted speed measure, mitigate the concern that the pattern observed in Panels A and B is driven by the diffusion of market-wide as opposed to relationship-specific supply chain information.

Turning to the control variables, we find that firm size of both trading partners and the number of analysts covering supplier firms are positively related to the speed of supply-chain information diffusion. Further, we find that information diffuses more slowly when customers experience negative earnings shocks. This result is consistent with Hong, Lim, and Stein (2000) who show that bad news travels more slowly than good news. Finally, we find that variables representing relationship strength are not associated with the speed of information diffusion along supply chains.

Although the results in this section are consistent with the hypothesis that the existence of market participants that simultaneously pay attention to both customers and suppliers increases the speed of supply-chain information diffusion, potential concerns with endogeneity bias make it difficult to identify a causal link. One possibility is that analysts may be more likely to dual-cover customer-supplier pairs that have closer economic links, such that the observed positive association between analyst dual-coverage and the speed of supply-chain information diffusion may be the result of an endogenous selection effect. Similarly, omitted common factors, such as the geographic location of firms and market participants, might affect both the speed of supply-chain information diffusion and the attention of market participants at the same time. We address this concern in the next section.

4. Natural Experiment: Regional Flu Epidemics and Market Participant Attention

To address concerns about endogeneity, we use a natural experiment based on regional flu epidemics to isolate the causal effect of market participant attention on the speed of supply-chain information diffusion.[12] Regional flu epidemics can have both direct and indirect effects on market participant attention. Direct effects are due to the fact that, analysts and institutional investors residing in regions affected by influenza epidemics are more likely to be infected with the flu. The common symptoms of flu, such as fever, pain, cough, and fatigue, may lead to a reduction in

[12] McTier, Tse, and Wald (2013) show that a high incidence of flu in the New York City area is associated with lower trading activity, reduced volatility, and lower market liquidity. Dong and Heo (2014) find that flu in the New York area affects analysts' forecast behavior. We control for the implications of these findings in our analysis.

attention and information processing capabilities of infected analysts and institutional investors. In addition to the analysts and institutional investors themselves, flu that affects their family members and flu that affects their colleagues, e.g., team members and support staff, may also slow information diffusion, even if the institutional investors and analysts themselves are not affected directly. Further, flu symptoms can last one to two weeks, which is sufficiently long to generate a significant impact on the analysts' or institutional investors' ability to process information around customers' earnings announcements. In sum, if analysts and investors in flu-affected regions are not able to pay as much attention to their work, flu epidemics provide a direct and exogenous shock to the attention of key market participants that analyze supply chain information. In effect, these tests allow us to hold dual-coverage and cross-holding constant, while comparing the speed of information diffusion at different times depending on the occurrence of 'peak flu' episodes in different regions of the U.S.

To identity periods of peak flu activity, we rely on weekly healthcare and flu exposure records, from 1997 to 2014, provided by the National Respiratory and Enteric Virus Surveillance System (World Health Organization (WHO)/NREVSS) and the Center for Disease Control and Prevention (CDC). Both datasets divide the flu data into ten major geographical regions defined by the U.S. Department of Health & Human Services (HHS). This allows us to identify the analysts and brokerages with dual-coverage, and the institutional investors with cross-holdings, that are exposed to regional flu epidemics. Following Dong and Heo (2014) we use the 'percentage of flu tests with positive results' from WHO/NREVSS and 'the percentage of patient visits to healthcare provider for influenza-like illness' from CDC as our two measures of flu epidemics.

[Insert Table 3 Here]

Diagrams in Figure 1 and statistics in Table 3 show time-series and cross-sectional properties of our two flu measures, respectively. We observe two clear patterns. First, although flu activity is typically clustered in winter and early spring, the severity and the duration of flu activity varies significantly across years. Second, although regions with higher population densities are more likely to be hit by the flu, the region with the most significant flu activity also varies over time. These two patterns in flu activity, while highlighting the importance to control for seasonality effects in our tests, also ensure sufficient time-series and cross-sectional variation in our identification strategies.

Our first set of tests focus on peak flu activity in Region 2 (New York and New Jersey) to study the causal effect of analyst and broker dual-coverage on the speed of supply-chain information diffusion. Because most Wall Street financial analysts live and work in this geographic region,[13] we conjecture that analysts are most likely affected by peak flu activity in the New York Region. To the extent that dual-covering analysts and brokers reside outside of this region and are not otherwise affected by the flu, this assumption works against finding a limited attention affect through analyst and broker dual-coverage. In our next set of tests, we use information pertaining to the exact locations of institutional investors, provided in the FactSet LionShares Ownership File, to examine the effect of peak flu activity in various regions on the speed of information diffusion through the institutional cross-holdings channel.

4.1. Flu Incidence in NYC Area, Analyst/Broker Dual-Coverage, and the Speed of Information Diffusion

[13] According to a subsample of analysts who reported their locations on FINRA.org, around 60% of financial analysts are located in the New York area.

To analyze the effect of flu epidemics on analysts and brokerage firms, we augment Equation (3) by interacting the dual-coverage variables with measures of flu incidence in the New York City area in the following specification:

$$Speed_{ijt} = \alpha + \beta_1 * X_{ijt} + \beta_2 * Flu\ in\ NYC_t + \beta_3 * (X_{ijt} \times Flu\ in\ NYC_t) + Z'_{it}\delta_1 + Z'_{jt}\delta_2 + R'_{ijt}\delta_3 + E'_{it}\delta_4 + \gamma_{ij} + \theta_t + \epsilon_{ijt} \quad (4)$$

where the control variables are the same as in Equation (3). X_{ijt} indicates either analyst dual-coverage or broker dual-coverage and $Flu\ in\ NYC_t$ is one of our measures of peak flu activity in the New York region during the week of the customer's earnings announcement. We employ two measures of flu incidence in our tests: *Flu in NYC 1* represents the "ILI" measure for the New York/New Jersey area, i.e. the percentage of patient visits to medical care providers for 'influenza like illness symptoms' as reported by the Center for Disease Control (CDC). *Flu in NYC 2* is the 'percentage of flu tests with positive results' in the New York/New Jersey, as collected and reported by WHO/NREVSS laboratories. By including an additional interaction term between analyst/broker dual-coverage and NYC flu incidence, this model is essentially equivalent to a triple-difference regression: the relationship and time fixed effects subsume any fixed differences between relationship-pairs and time-series variation affecting all relationship pairs. Hence, β_2 captures the difference-in-difference effect of flu epidemics in New York on the speed of information diffusion, whereas β_3 captures the triple-difference effect showing whether the flu has a differential effect on the speed of information diffusion when the flu affects dual-covering analysts or brokers.

[Insert Table 4 Here]

Table 4 reports our estimates of Equation (4). Panels A and B show the results related to analyst dual-coverage and broker dual-coverage, respectively. Consistent with our findings in

Table 2, the results in Panel A of Table 4 confirm that analyst dual-coverage has a positive and statistically significant impact on the speed of information diffusion, even after we include flu incidence measures and interaction effects. Using the unadjusted speed measure as our dependent variable, the coefficients of *Analyst Dual Cov* are 0.00681 and 0.00549 in Columns (1) and (2), which are comparable to those reported in Panel A of Table 2. Both coefficients are statistically significant at the 1% level. We find a negative effect of peak flu episodes in the NYC region on the speed of information diffusion, e.g., -0.00283 in Column (1) and -0.00110 in Column (2). This corresponds to a 1.64% and 3.86% decrease in the unadjusted speed of information diffusion measure for a one standard deviation increase in the 'ILI' measure and the 'percentage positive tests' measure for flu incidence respectively, relative to the unconditional sample mean. These results suggest that overall informational efficiency is reduced when the NYC area is adversely affected by flu incidence.

The key finding in Panel A of Table 4 is that limited attention due to flu incidence in the NYC area affects the speed of supply-chain information diffusion through analyst dual-coverage. As reported in Columns (1) and (2), the coefficient estimates on the interaction terms between the NYC flu episodes and analyst dual-coverage are both negative and statistically significant at the 1% level. The coefficient of *Analyst Dual Cov×NYC Flu 1* in Column (1), -0.00133, implies that, while one additional dual-covering analyst is associated with an increase of 0.00681 in the unadjusted speed measure unconditionally, this effect is reduced by 29.10%[14] for a one standard deviation increase in the "influenza like illness" measure and by 24.43% for a one standard

[14] The standard deviation of the "influenza like illness" flu measure reported in Region 2 (NYC) as reported in Table 3 is 1.49. Hence the percentage reduction is calculated as $1.49 * -\frac{0.00133}{0.00681} = -0.2910$. Economic magnitudes of coefficients in other tests are interpreted based on similar computations.

deviation increase in the "percentage positive tests" flu measure. In Columns (3) and (4), we repeat these tests using the market-adjusted speed measure as dependent variable. Our results are similar: the positive effect of analyst dual-coverage on the speed of information diffusion is strongly mitigated when the NYC area is affected by flu epidemics. Taken together, these results provide novel evidence that limited attention of financial analysts reduces informational efficiency in general and the speed of supply-chain information diffusion in particular.

In Panel B of Table 4 we repeat the same analysis focusing on the interaction effect between broker dual-coverage and flu activity in the NYC area. We find results similar to those reported in Panel A. Consistent with our previous results we find that broker dual-coverage is positively associated, and NYC peak flu episodes are negatively associated with the speed of supply-chain information diffusion. The coefficient estimates on the interaction term of flu in the NYC area and brokerage dual-coverage are negative, consistent with a reduction in the speed of information transmission due to flu-induced inattention. The coefficient of *Broker Dual Cov* × *NYC Flu 1* in Column (1), -0.000654, indicates a 28.41% reduction for a one standard deviation increase in the "ILI" measure of flu incidence in the New York region, based on the unconditional effect of broker dual-coverage. Similarly, a one standard deviation increase in the "percentage positive tests" flu measure corresponds to a 14.77% reduction relative to the unconditional coefficient of broker dual-coverage.

This pattern is consistent with the notion that both analyst and broker dual-coverage facilitate the diffusion of information along the supply chain. However, since the probability that a dual-covering analyst is affected by the flu is higher than the chance that two analysts from the same brokerage are simultaneously affected by the flu, we would expect the interaction effect between peak flu episodes and analyst dual-coverage to be stronger than the interaction effect between flu episodes and broker dual-coverage. Our results are consistent with this conjecture. Finally, we note that all of the findings in Table 4 are robust to our alternative definitions of diffusion speed.[15]

4.2 Local Flu Activity, Institutional Cross-Holding, and the Speed of Information Diffusion

Our previous tests reported in Table 4 focus on flu incidence in the NYC area since it is where most analysts reside and work. As noted earlier, to the extent that analysts located outside the NYC area are not affected by the flu, these tests will underestimate the effect of reduced attention on the speed of information diffusion. In addition, these tests are less powerful in that they do not capture the effect of flu incidence in other regions. In this section, we study the interaction effect of institutional cross-holding and *local* flu incidence (i.e., flu in the region where the institutional investors are located) on the speed of supply-chain information diffusion. In addition to avoiding the concerns listed above, focusing on local flu allows us to alleviate remaining endogeneity concerns related to seasonal patterns, as we are comparing institutional investors with cross-holdings at the same point in time exploiting differences in flu epidemics due to different locations.

To measure the effect of local flu incidence on cross-holding institutional investors, we rely on the exact location of the institutional investors as reported in the FactSet LionShares Ownership file. Figure 2 provides an overview of the geographical distribution of institutional investor locations across all ten CDC regions. The figure shows that institutional investors are mainly located in major financial centers dispersed in different CDC regions, such as New York

[15] In tests not tabulated for brevity we further confirm that our results also hold if we specify both analyst and broker dual-coverage as well as flu incidence in the New York region as dummy variables.

City (Region 2), Boston (Region 1), Chicago (Region 5), San Francisco and Los Angeles (Region 9).

To test the effect of reduced attention of cross-holding institutional investors on the speed of information diffusion, we estimate regressions of the following specification,

$$\begin{aligned} Speed_{ijt} = \alpha + \beta_1 * X_{ijt} + \beta_2 * Cross\ Own\ Location\ Flu_t \\ + \beta_3 * (X_{ijt} \times Cross\ Own\ Location\ Flu_t) \\ + Z'_{it}\delta_1 + Z'_{jt}\delta_2 + R'_{ijt}\delta_3 + E'_{it}\delta_4 + \gamma_{ij} + \theta_t + \epsilon_{ijt} \end{aligned} \quad (5)$$

where X_{ijt} captures institutional cross-holdings and all controls are defined similarly as in Equations (3) and (4). We again rely on the same two measures of flu incidence, the "influenza like illness" measure and the "percentage of positive flu tests", but here they are measured in the specific location of each institutional investor. Thus, in contrast to the tests reported in Table 4, β_2 captures the difference-in-difference effect of local flu (as opposed to flu in NYC) on the speed of information diffusion. The coefficient of the key variable of interest, β_3, estimates the triple-difference effect of flu exposure on cross-holding institutional investors.

[Insert Table 5 Here]

Table 5 reports our estimates of Equation (5). Consistent with earlier results reported in Table 2, the unconditional effect of institutional cross-holding on the speed of information diffusion is still positive and statistically significant at the 1% level. For example, when we use the unadjusted speed measure as the dependent variable, the coefficients of *Cross Own* are 0.00769 and 0.00760 in Columns (1) and (2), respectively. This is equivalent to a 3.00% increase in the speed of information diffusion associated with adding one additional cross-holding institutional investor, relative to the unconditional sample mean. Not surprisingly, we find that local flu incidence periods do not affect the overall information efficiency in financial markets in the same manner as flu epidemics in the NYC area (as reported in Table 4). The coefficient of *Cross Own Location Flu 1* is positive and statistically insignificant. In contrast, the coefficients of *NYC Flu 1 and 2* are negative and statistically significant at the 1% level in all specifications reported in Table 4.

The key finding in Table 5 is that the positive impact of institutional cross-holding on the speed of information diffusion is significantly reduced when active institutional investors with cross-holdings are located in regions strongly affected by the flu. For example, the coefficient estimate on the interaction term in Column (1), *Cross Own* × *Cross Own Flu 1*, is -0.00289, which is statistically significant at the 1% level. This result suggests that, when the locations of cross-holding institutional investors are affected by the flu (i.e., the "ILI" measure increases by one standard deviation), the effect of institutional cross-holding on the speed of supply-chain information diffusion is reduced by 54.11%, relative to the unconditional mean. Similarly, using our second measure of flu incidence, the 'percentage of positive flu tests' as reported in Column (2), the positive effect of institutional cross-ownership on the speed of information diffusion is reduced by 47.00% when the flu incidence measure increases by one standard deviation. Similar to our previous tests, we repeat our above regressions using the market-adjusted speed measure as an alternative dependent variable. Results are reported in Columns (3) and (4). Again, our results are robust to various combinations of alternative speed measures and local flu measures.

Although institutional investors are distributed across different CDC regions, it is still true that the NYC area accommodates the highest number of institutional investors. Therefore, one concern is that institutional investors and financial analysts might share a similar geographical distribution. To address this concern, we interact institutional cross-holding with the NYC flu incidence measure used in Table 4. The results are reported in Columns (5) and (6). Consistent with our previous results in Table 4, we show that the flu epidemics in the NYC area are associated with a significant reduction in the speed of supply-chain information diffusion. However, the coefficients of the interaction terms of NYC flu with institutional cross-holding are not statistically significant in both columns. This result verifies our main message from Table 5: the interaction effect of institutional cross-holding and the peak flu activity would only affect the speed of information diffusion when the flu hits these cross-holding institutional investors locally.

5. The Importance of Speed of Information Diffusion for Investors and Firms

5.1. Speed of Information Diffusion and the Customer Momentum Investment Strategy

Cohen and Frazzini (2008) show that a "customer momentum strategy", where investors simultaneously buy stocks of supplier firms with high lagged customer returns and sell short stocks of supplier firms with low lagged customer returns, earns positive and significant abnormal returns. A necessary condition to implement this strategy successfully is that investors are able to identify customer-supplier relationships where information diffuses slowly from customers to suppliers. Therefore, investors can benefit from constructing and employing measures that can accurately capture the speed of supply-chain information diffusion.

We note that proxies for the speed of supply-chain information diffusion, such as analyst dual-coverage, broker dual-coverage, and institutional cross-holding have been recognized in previous literature. However, our speed measure has several advantages over these proxies. First, the proxies do not actually measure speed directly, i.e., by observing analyst dual-coverage, broker dual-coverage, and the institutional cross-holding, we cannot tell how fast information diffuses from customers to suppliers. Second, it is not easy to identify a subsample of customer-supplier relationships with slow information diffusion given the distributional properties of these proxies. For example, as shown in Table 1, more than 75% of customer-supplier relationships have no analyst dual-coverage. Therefore, it is not possible to identify a smaller subsample (e.g., a quintile or a quartile of the full sample) with slower information diffusion based on analyst dual-coverage. Third, as reported in Table 2, analyst dual-coverage, broker dual-coverage, and institutional cross-holding carry incremental information in explaining the speed of supply-chain information diffusion. These incremental effects are captured by our speed measure but cannot be captured in portfolio sorts using various combinations of the proxies for speed. Finally, analyst dual-coverage, broker dual-coverage, and institutional cross-holding have very little time-series variation. Portfolios sorted by these proxies will not be able to capture time-series variation in the speed of supply-chain information diffusion.

In this subsection, we provide evidence on the ability of our speed measure to identify more profitable customer momentum strategies. In addition, we also compare how our measure does in identifying profitable strategies relative to another proxy for the speed of supply-chain information diffusion: firm size. We use firm size as a benchmark proxy for the speed of information diffusion for two reasons. First, firm size captures many well-known factors that affect speed of information diffusion, such as corporate transparency and information environment. Second, firm size is a continuous and time-varying variable that can easily be used to sort firms into multiple groups. For brevity, we use the market-adjusted speed measure as a representative for our speed measures in this subsection.

Table 6 reports the results of our analysis. We follow Cohen and Frazzini (2008) in developing our testing procedure. Specifically, at the beginning of each calendar month *t*, stocks of suppliers are first sorted into three equal groups by the market-adjusted speed measure based on four earnings announcements before month *t*. For our comparison tests, supplier stocks are similarly sorted by market capitalization at the end of month *t-1*. In each of the three sub-groups, supplier stocks are then sorted into five quintile portfolios based on the (portfolio) returns of their principal customers at the end of the previous month, i.e., month *t-1*.[16] All stocks are equally weighted within a given portfolio and the portfolios are reconstituted every calendar month. In an untabulated test, we repeat these tests using value-weighted portfolios and find similar results.

[Insert Table 6 Here]

Consistent with our expectation, the results in the Columns 1, 2, and 3 of Panel A which are based on portfolio sorts using firm size as a proxy for diffusion speed, show that the customer momentum strategy generates higher returns among small suppliers. For suppliers in the small size group, the customer momentum strategy yields an average monthly return of 0.967%. For firms in the large size group, the average monthly hedging portfolio return is 0.479%. The difference in hedging portfolio returns between these two groups is 0.488%, which is statistically significant at the 5% level.

Columns 4, 5 and 6 of Panel A report results of customer momentum strategies when grouped by our market-adjusted speed measure. Three findings are of particular interest. First, for firms within the slow information diffusion group (Column 4), the average hedging portfolio return is 1.197%, which is 23.8% higher than that for the small size group in Column 1. Second, the hedging portfolio return in the fast information diffusion group shown in Column 6 becomes statistically insignificant. Third, the difference in hedging portfolio returns between the slow information diffusion group (1.197%) and the fast information diffusion group (0.276%) is

[16] When a supplier has more than one principal customer, we generate a sales-weighted portfolio of customers and use the lagged returns of the customer portfolio to sort supplier firms.

0.921%, which is more than twice as large as the difference (0.488%) between the small size group and the large size group; the difference of 0.433% is statistically significant at the 5% level. Taken collectively, these results suggest that our measure of diffusion speed can help to identify a "sharper" customer momentum strategy.

We repeat the above tests based on alphas after adjusting for the market factor, the Fama-French (1993) size and value factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Results are reported in Panel B. Our results remain the same after removing the impact from common risk and firm characteristic factors. In particular, our speed measure generates higher alphas in both the long and short positions within the slow information diffusion group, relative to those in the small size group.[17] This result confirms that our speed measure helps generate more profitable customer momentum strategies than other more "coarse" measures, such as size of supplier firms.

5.2. Speed of Information Diffusion and the Price-Feedback Effect of Firm Investment Decisions

Chen, Goldstein, and Jiang (2007) show that managers learn from their own stock prices when making investment decisions. Foucault and Frésard (2014) and Williams and Xiao (2016) provide evidence for a broader price-feedback channel suggesting that firms also use information contained in stock prices of closely-related firms, such as peers and principal customers. In this section, we examine how the speed of information diffusion from customer to supplier stock prices can potentially affects supplier managers' reliance on their own versus their customers' stock prices as information sources.

[17] The improvement of alpha in the long side might be more interesting and meaningful to practitioners given it is less costly to build a long position than a short position.

If all customer-related information is instantaneously incorporated into suppliers' stock prices, managers of suppliers who pay attention to information of their customers only have to consider their own stock prices when learning about investment opportunities. On the other hand, when information diffuses slowly from customers to suppliers, supplier stock prices do not reflect information contained in customer stock prices in a timely and efficient manner. Therefore, to the extent that supplier managers can learn from prices, they would have to rely more heavily on customer stock prices and less heavily on their own stock prices to guide their optimal decision-making in corporate investments.

Following Foucault and Frésard (2012), we exclude financial firms (SIC codes 6000 to 6999) and utilities (SIC codes 9000 to 9999) from this analysis since their investments are largely dependent on regulatory and capital requirements. To test the above hypothesis, we estimate investment-Q sensitivity regressions at the quarterly frequency as follows:

$$
\begin{aligned}
I_{it} &= \alpha + \beta_1 * Q^{sup}_{i,t-1} + \beta_2 * Q^{cus}_{j,t-1} + \beta_3 * Speed_{i,t-1} \\
&+ \beta_4 * \left(Q^{cus}_{j,t-1} \times Speed_{i,t-1}\right) + \beta_5 * \left(Q^{sup}_{j,t-1} \times Speed_{i,t-1}\right) \\
&+ interaction\ terms + other\ controls + \gamma_{ij} + \theta_t + \epsilon_{ijt} \qquad (7)
\end{aligned}
$$

where I_{it} represents the asset growth or capital investment of supplier *i* in quarter *t*; $Q^{sup}_{i,t-1}$ and $Q^{cus}_{j,t-1}$ are the one-quarter lagged Tobin's Q of the supplier and customer firm respectively; and $Speed_{i,t-1}$ is the speed of information diffusion along the supply chain, which we measure using our market-adjusted speed measure. We include lagged leverage, cash holdings, operating cash flows, return on assets, and sales turnovers of suppliers as additional control variables. Since we are investigating the investment-Q sensitivity in this test, we also include the interaction terms between these control variables and lagged Tobin's Q of suppliers as independent variables. This is in line with Edmans, Jayaraman, and Schneemeier (2017) who point out that investment-Q sensitivity regressions estimate a slope, not a level, coefficient, and adequate controls therefore need to include interactions with Q. In addition, we incorporate relationship and quarterly time fixed effects in our test specifications. Definitions of all variables are provided in Appendix Table I. Following Chen, Goldstein, and Jiang (2007) we use the percentage change in assets (Panel A) as well as capital expenditures scaled by lagged book value of total assets (Panel B), as our measures of suppliers' investment I_{it}. The results from these regressions, reported in Table 7, yield two main insights.

[Insert Table 7 Here]

First, we confirm the findings of Chen, Goldstein, and Jiang (2007) and Williams and Xiao (2016) at the quarterly frequency. If suppliers rely on their own stock prices to guide their investment decisions, we should find a positive relationship between supplier investments and supplier Tobin's Q, i.e., $\beta_1 > 0$, after controlling for cash constraints and access to capital. If managers of suppliers also use information contained in customer stock prices as suggested by Williams and Xiao (2016) and information diffusion from customers to suppliers is not instantaneous, we would expect a positive sensitivity of suppliers' investment to customers' Tobin's Q, i.e. $\beta_2 > 0$. Our results are consistent with these conjectures. For example, in Column (1) of Panel A, the estimates of β_1 (the coefficient of *Tobin's Q Supplier*) and β_2 (the coefficient of *Tobin's Q Customer*) are 0.0623 and 0.00822, respectively. Both coefficients are statistically significant at the 1% level. This pattern is observed in all specifications irrespective of whether we use supplier asset growth or capital expenditures as the dependent variable in the regressions.

Second, and more importantly, our results in Columns (2)-(4) suggest that the speed of supply-chain information diffusion determines the weights that supplier managers who learn from prices assign to information contained in stock prices of their customers and their own firms when making investment decisions. The interaction effect of Supplier-Q and $Speed_{i,t-1}$ in Column (3) is positive and statistically significant at the 5% level, indicating that the faster customer-related information diffuses from the customer to the supplier, the more strongly supplier firm managers rely on their own stock prices to inform subsequent investment decisions. Similarly, the interaction effect of customer-Q and $Speed_{i,t-1}$, as shown in Column (3), is negative and significant. Consistent with the previous interpretation, this result suggests that a feedback effect from customers' stock prices to suppliers' investment is stronger (weaker) when information diffuses along the supply chain slower (faster). The coefficient estimates are robust for both measures of investment and statistically significant at the 5% level. In Column (4), where we include both Q-interaction terms, the results remain robust. The coefficient estimates on Supplier-Q * $Speed_{i,t-1}$ and Customer-Q * $Speed_{i,t-1}$ of 0.0119 and -0.0105 suggest that for a one standard deviation increase in *Speed*, the investment-Q (supplier) sensitivity increases by 4.09% and the investment-Q (customer) sensitivity decreases by 21.31%.

Considering the quarterly change in capital expenditure as an alternative proxy for investments in Panel B of Table 7 we find similar results. The regression coefficient on the interaction effect of supplier-Q and speed of information diffusion is positive (0.0030) and statistically significant at the 1% level. This result suggests that a one standard deviation increase in diffusion speed is associated with an increase in investment-Q (supplier) sensitivity of 6.09% (=0.2071*0.0030/0.0102), consistent with our findings in Panel A.

Taken together our results suggest that the speed of supply-chain information diffusion may provide important guidance to supplier managers on the extent to which they should incorporate additional information contained in customers' stock prices in their decision-making.

Our results suggest that knowledge of the speed of information diffusion can have real economic consequences.

6. Conclusion

Based on the methodology of Hou and Moskowitz (2005), we develop a new measure of the speed of information diffusion along supply chains. Our measure is computed based on daily stock returns of customers and suppliers around the earnings announcement dates of customer firms. We find that the level of attention of key market participants, such as financial analysts and active institutional investors, is highly correlated with the speed of supply-chain information diffusion. Specifically, we find that the speed of information diffusion from customers to suppliers is faster when there exist analyst dual-coverage, broker dual-coverage, and institutional cross-holding of customers and suppliers.

Our findings on the correlation between the attention of key market participants on supply-chain relationships and the speed of information diffusion along supply chains are vulnerable to various endogeneity concerns, e.g., these results could be explained by reverse causality or driven by common unobservable economic factors. To address these endogeneity concerns, we employ an identification strategy based on regional flu epidemics. The exogenous shocks to attention generated by flu epidemics allow us to establish the causality that limited attention of market participants on supply-chain relationships adversely affects the speed of information diffusion along supply chains.

We demonstrate that our measure of supply-chain information diffusion speed can be useful to both investors and corporate managers. We show that our speed measure helps investors generate "sharper" customer momentum strategies by accurately identifying relationship-pairs with slow information diffusion. We also demonstrate that our measure can potentially guide corporate managers about how they should assign weights on stock prices of their own firms and their customer firms in making optimal corporate decisions.

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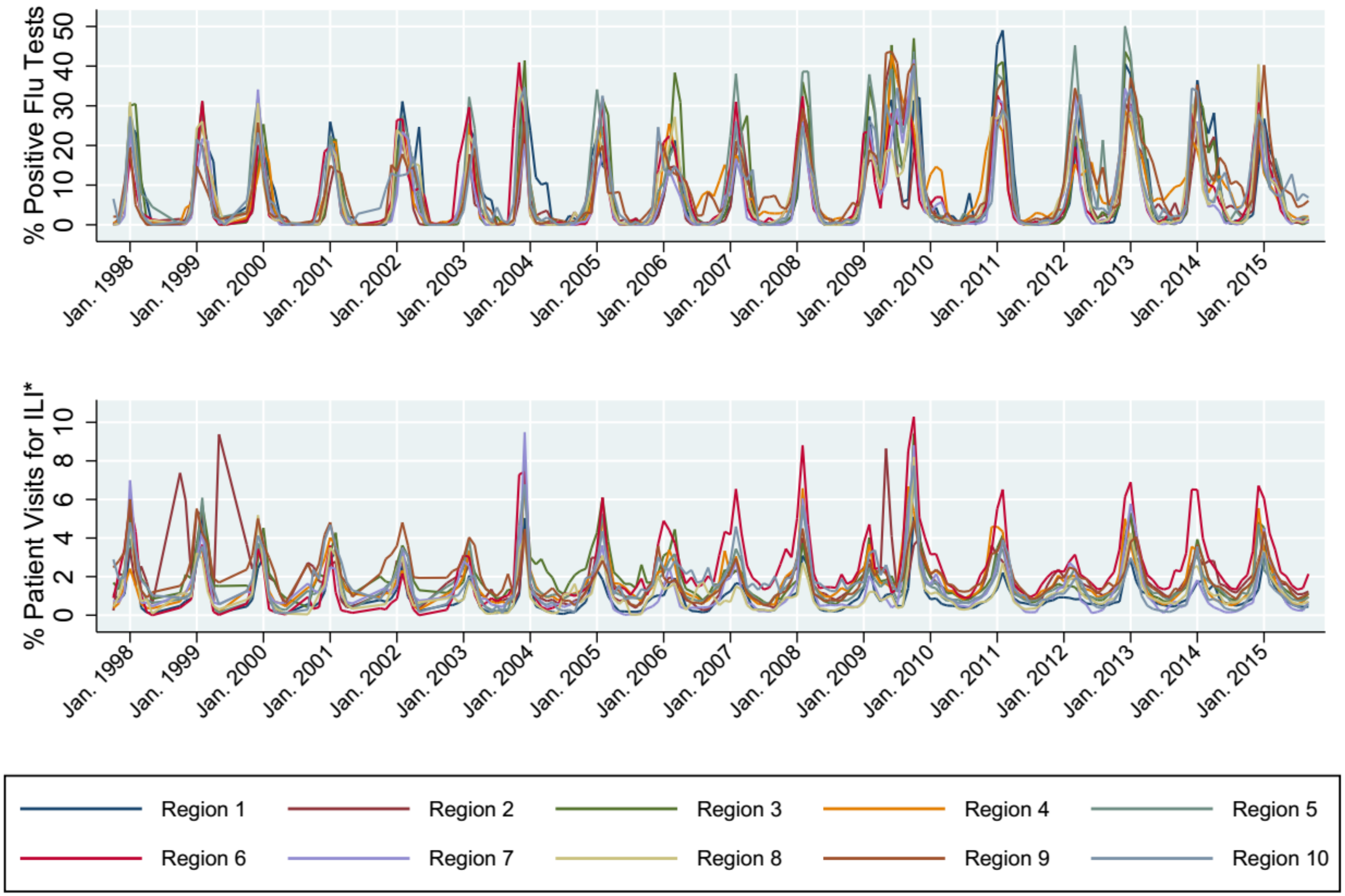
Appendix I. Definition of Variables

Variable	Short Description	Detailed Comments
R^2 (K lags)	Magnitude of Information Diffusion from customer to supplier (R^2 of return regression)	R^2 (K lags) is estimated using daily returns of the supplier and customer firm (with K lags) around the customer's earnings announcement (EA) ranging from 10 days before to 30 days after the EA. We use a regression model of the following form: $Ret_{i,t}^{sup} = \alpha_i + \sum_{k=0}^{K} Ret_{i,t}^{cus} + \epsilon_{i,t}^{sup}$. (Data source: CRSP)
Log(S_{04})	Speed of Information Diffusion from customer to supplier around customer's earnings announcement	We define 'Information Diffusion Speed' as the ratio of the R^2 of the supplier's daily returns on the customer's daily returns with zero and five daily lags respectively, $S_{04} = R^2_{0\,lags}/R^2_{4\,lags}$. We transform this variable using the logarithm, $logS_{04} = \log\left(S_{04}/(1 - S_{04})\right)$. (Data source: CRSP)
Flu in NYC 1	Flu incidence measure in the NYC region	'Influenza like illness (ILI)' measure for the region of interest, New York and New Jersey, during the week of the customer's earnings announcement. "ILI" represents the number of patient visits to healthcare providers for flu like symptoms collected by the Center for Disease Control's (CDC). (Data source: Center for Disease Control and Prevention)
Flu in NYC 2	Flu incidence measure in the NYC region	Similar to *Flu in NYC 1* using the 'percentage of flu tests with positive results' measure for the region of interest, New York and New Jersey, collected by collaborating laboratories of the World Health Organization (WHO) and NREVSS. (Data source: National Respiratory and Enteric Virus Surveillance System (NREVSS))
Cross Own Location Flu 1	Flu in region of institutional owner's location	'Influenza like illness (ILI)' measure for the region in which the biggest institutional cross-holding (owns largest proportion of shares) is located, during the week of the customer's earnings announcement. The location of the institutions is obtained from the Factset Institutional Ownership database. The regions are defined similar to *Flu in NYC 1*, as the 10 HHS regions used by the CDC. "ILI" represents the number of patient visits to healthcare providers for flu like symptoms collected by the Center for Disease Control's (CDC). (Data source: Center for Disease Control and Prevention)
Cross Own Location Flu 2	Flu in region of institutional owner's location	Similar to *Cross Own Location Flu 1* using the 'percentage of flu tests with positive results' measure, collected by collaborating laboratories of the World Health Organization (WHO) and NREVSS. (Data source: National Respiratory and Enteric Virus Surveillance System (NREVSS))
Analyst Dual Cov	Dual-coverage by individual analysts	Number of analysts covering both the supplier and customer firm in the given year. (Data source: IBES)
Broker Dual Cov	Dual-coverage by brokerage firm	Number of brokerage firms covering both the supplier and customer firm in the given year. (Data source: IBES)
Inst Cross Hold	Institutional cross-holding	Number of institutional investors owning a significant portion (>1% of outstanding stocks) of both the customer and supplier firm in the given quarter. (Data source: Thomson Reuters Ownership)

Analysts Customer (Supplier)	Analyst following of the customer (supplier)	Number of analysts covering the customer and supplier firm respectively in the given quarter. (Data source: IBES)
log(MV) Customer (Supplier)	Firm size customer (supplier)	Logarithm of the market capitalization of the customer (supplier) firm. (Data source: Compustat and CRSP)
Change Assets Supplier	Asset Size Change (quarterly)	Change in assets at the quarterly frequency scaled by beginning-of-quarter assets (%), following Chen, Goldstein, and Jiang (2007). (Data source: Compustat Quarterly)
CapEx Supplier	Capital Expenditure (quarterly)	Capital expenditure at the quarterly frequency, scaled by beginning-of-quarter assets (%), following Chen, Goldstein, and Jiang (2007). (Data source: Compustat Quarterly)
Assets Inverse Supplier	Firm size (quarterly)	(Inverse of) book value of assets at quarterly frequency (Data source: Compustat Quarterly)
Tobin's Q Supplier (Customer)	Tobin's Q (quarterly)	Tobin's Q for supplier and customer at the quarterly frequency following Chen, Goldstein, and Jiang (2007) (CGJ), q_cqj = (mvq + atq – ceqq)/atq, where mvq is the market value (shares outstanding* crsp stock price at the end of the quarter), and ceqq is the book value of equity. (Data source: Compustat Quarterly)
KZ 4 Index Supplier	Kaplan-Zingales Index with 4 variables (excluding Q) (quarterly)	Kaplan-Zingales Index of financial constraints with 4 elements, following Chen, Goldstein, and Jiang (2007), computed as kz_4 = -1.001909*(cf /atq(t-1)) + 3.139193*(debt /total_cap) - 39.3678*div/atq(t-1) - 1.314759*cheq/atq(t-1), where cf is the cash flow (income before extraordinary item + depreciation and amortization), debt is current and long-term debt, total_cap is total capital (debt + shareholder's total equity), div are the total dividends paid, and cheq is cash and short-term items, all at the quarterly frequency. (Data source: Compustat Quarterly)
Cash Flow Supplier	Cash Flow (quarterly)	Cash flow at the quarterly frequency, computed as income before extraordinary item + depreciation and amortization, scaled by lagged assets. (Data source: Compustat Quarterly)
ROA Supplier	Operating earnings (quarterly)	Return to assets (%), computed as net income scaled by asset size at the quarterly frequency. (Data source: Compustat Quarterly)
Sales Turnover Supplier	Sales Turnover (quarterly)	Sales revenue divided by total asset values (%). (Data source: Compustat Quarterly)
abs(SUE) customer	Absolute value of standardized unexpected earnings	Abs(Mean quarterly earnings forecast – actual quarterly earnings)/stock price of the customer firm. (Data source: IBES)
EPS Forecast Dispersion	Analyst forecast dispersion	Standard deviation of analysts' earnings forecasts for customer firm. (Data source: IBES)
Pct of Customer Sales	Relationship intensity	Sales of supplier to customer firm/ Total sales of supplier firm. (Data source: Compustat Segment Files and Compustat)
Pct of Customer COGS	Relationship intensity	Sales of supplier to customer firm/ Total Cost of Goods Sold of customer. (Data source: Compustat Segment Files and Compustat)

Figure 1: Time Series of Flu Measures



Data collected by WHO/NREVSS Collaborating Laboratories. Obtained from Center for Disease Control (CDC) website.
*ILI: Influenza-Like-Illness Symptoms.

Figure 2: Location of Institutional Investors in CDC Regions

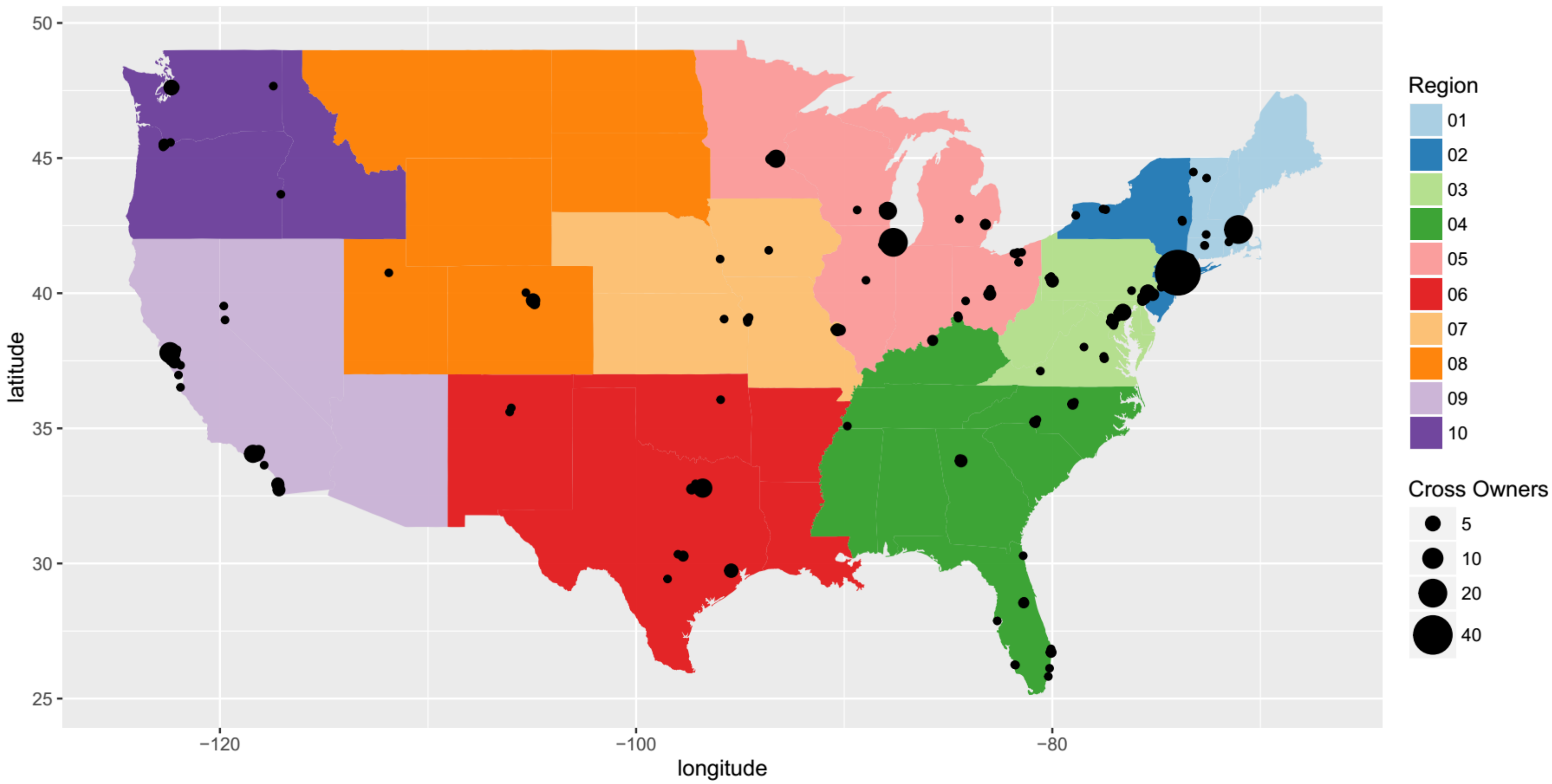


Table 1: Summary Statistics

This table presents summary statistics at the quarterly frequency of all dependent and independent variables used in this paper. Our sample period is from 1983 to 2013. We exclude pair-quarters that do not have at least 25 daily return observations around the customer's earnings announcements. Panel A of this table shows summary statistics for the customer-supplier relationships, the customer firms, and the supplier firms in our sample. Panel B presents summary statistics related to the customer firms' quarterly earnings announcements. Panel C reports summary statistics of various speed measures that we use in this paper. We winsorize all accounting related variables at the 1% level. Detailed definitions of all variables are provided in Appendix I.

Panel A. Customer-Supplier Relationships

Variables	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Relationship Variables:						
Analyst Dual Cov	139925	0.750	1.795	0	0	0
Broker Dual Cov	139925	2.926	4.396	0	1	4
Inst Cross Hold	84797	0.738	1.255	0	0	1
Analyst Dual Cov Dummy	139925	0.248	0.432	0	0	0
Broker Dual Cov Dummy	139925	0.545	0.498	0	1	1
Inst Cross Hold Dummy	84797	0.356	0.479	0	0	1
Pct of Supplier Sales	114007	0.195	0.152	0.106	0.150	0.230
Pct of Customer COGS	113074	0.012	0.029	0.000	0.002	0.008
Customer Variables:						
Assets Customer (Mil)	139317	51283.330	73004.160	5820.134	20021.000	57814.020
ln(Assets) Customer	139317	9.735	1.740	8.669	9.905	10.965
Mkt Cap Customer (Mil)	138856	41292.730	60046.610	4288.505	16000.800	47678.700
ln(Mkt Cap) Customer	138856	9.487	1.765	8.364	9.680	10.772
Analysts Customer	139832	20.096	10.986	13.000	21.000	28.000
ln(1+Analysts) Customer	139832	2.752	1.004	2.639	3.091	3.367
Supplier Variables:						
Assets Supplier (Mil)	139925	978.025	2226.654	39.446	146.518	684.246
ln(Assets) Supplier	139925	5.145	1.932	3.700	4.994	6.530
Mkt Cap Supplier (Mil)	138660	1020.135	2428.268	34.854	152.741	676.840
ln(Mkt Cap) Supplier	138660	5.095	2.013	3.579	5.035	6.519
Analysts Supplier	139869	4.582	5.959	0.000	2.000	7.000
ln(1+Analysts) Supplier	139869	1.175	1.057	0.000	1.099	2.079

Panel B. Customers Earnings Announcements

Earnings Announcement Variables:						
Variables	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
abs(SUE)	139925	0.003	0.008	0.000	0.001	0.003
SUE Neg (y/n)	139925	0.328	0.469	0.000	0.000	1.000
STD(EPS Forecast)	137758	0.047	0.063	0.010	0.020	0.060

Panel C. Speed Measures

N	Mean	SD	Skew	Kurt	P5	P25	P50	P75	P95
Unadjusted Speed Measure									
140924	0.2564	0.2557	0.9431	2.8021	0.0015	0.0381	0.1667	0.4209	0.7838
Log-transformed Speed Measure									
140924	-1.9851	2.4602	-1.1376	5.7692	-6.5244	-3.2298	-1.6093	-0.3191	1.2881
Market Residuals Speed Measure									
140924	0.1874	0.2071	1.3662	4.2653	0.0010	0.0251	0.1081	0.2871	0.6344

Table 2. The Speed of Information Diffusion: Analyst Dual-Coverage, Broker Dual-Coverage, Institutional Cross-Holding

This table reports OLS regression estimates of the speed of information diffusion around the customer's quarterly earnings announcements (EA) as a function of analyst dual-coverage, broker dual-coverage, and institutional cross holding. The dependent variables in Panels A, B, and C are the speed measure based on raw returns, the log transformed speed measure based on raw returns, and the speed measure based on residual returns, respectively. Detailed definitions of dependent variables and independent variables are defined in Appendix I. We include relationship and quarterly time-fixed effects in all specifications. *t*-statistics in parentheses are computed based on standard errors clustered at the relationship level in all specifications. ∗, ∗∗ and ∗∗∗ indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Unadjusted Speed Measure

	Dependent Variable: Unadjusted Speed Measure				
	(1)	(2)	(3)	(4)	(5)
Analyst Dual Cov	**0.00531*** **				**0.00578*** **
	(3.36)				**(2.74)**
Broker Dual Cov		**0.00266*** **		**0.00248** **	
		(3.45)		**(2.54)**	
Inst Cross Hold			**0.00424*** **	**0.00427*** **	**0.00418*** **
			(2.89)	**(2.91)**	**(2.85)**
ln(1+ #Analysts Customer)	0.0000837	0.000184	-0.000562	-0.000942	-0.00127
	(0.03)	(0.06)	(-0.15)	(-0.26)	(-0.35)
ln(1+ #Analysts Supplier)	0.0132***	0.0119***	0.0200***	0.0167***	0.0180***
	(5.61)	(4.80)	(6.08)	(4.85)	(5.46)
ln(MV Customer)	0.00530**	0.00519**	0.00465	0.00472	0.00484
	(2.23)	(2.18)	(1.54)	(1.57)	(1.62)
ln(MV Supplier)	0.0174***	0.0171***	0.0199***	0.0192***	0.0195***
	(11.00)	(10.69)	(9.32)	(8.94)	(9.15)
abs(SUE)	-0.111	-0.106	-0.130	-0.132	-0.138
	(-1.34)	(-1.28)	(-1.15)	(-1.17)	(-1.23)
SUE Neg (y/n)	-0.00352**	-0.00362**	-0.00472**	-0.00479**	-0.00469**
	(-2.17)	(-2.24)	(-2.07)	(-2.10)	(-2.05)
STD(EPS Forecast)	-0.0340*	-0.0336	-0.0550*	-0.0565*	-0.0576*
	(-1.66)	(-1.64)	(-1.80)	(-1.85)	(-1.88)
Pct Sales Supplier	-0.00631	-0.00509	-0.000612	-0.00113	-0.00163
	(-0.62)	(-0.50)	(-0.04)	(-0.08)	(-0.12)
Pct COGS Customer	0.0646	0.0746	0.0665	0.0515	0.0412
	(0.83)	(0.97)	(0.72)	(0.56)	(0.45)
Intercept	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair	Pair
N	110969	110969	70747	70747	70747
R-sq	0.338	0.338	0.366	0.366	0.366
adj. R-sq	0.266	0.266	0.293	0.293	0.294

Panel B: Log Transformed Speed Measure

	Dependent Variable: Log Transformed Speed Measure				
	(1)	(2)	(3)	(4)	(5)
Analyst Dual Cov	**0.0335*** **				**0.0361** **
	(2.77)				**(2.42)**
Broker Dual Cov		**0.0200*** **		**0.0193** **	
		(3.22)		**(2.55)**	
Inst Cross Hold			**0.0292** **	**0.0294** **	**0.0289** **
			(2.39)	**(2.41)**	**(2.36)**
ln(1+ #Analysts Customer)	0.00880	0.00868	0.0182	0.0153	0.0138
	(0.30)	(0.30)	(0.59)	(0.49)	(0.45)
ln(1+ #Analysts Supplier)	0.0820***	0.0694***	0.122***	0.0964***	0.109***
	(3.46)	(2.80)	(4.00)	(2.98)	(3.56)
ln(MV Customer)	0.0517**	0.0510**	0.0536**	0.0542**	0.0548**
	(2.30)	(2.26)	(1.97)	(2.00)	(2.03)
ln(MV Supplier)	0.138***	0.135***	0.151***	0.145***	0.148***
	(8.85)	(8.57)	(7.45)	(7.15)	(7.32)
abs(SUE)	-1.050	-1.026	-0.955	-0.970	-1.005
	(-1.29)	(-1.26)	(-0.94)	(-0.95)	(-0.99)
SUE Neg (y/n)	-0.0363**	-0.0371**	-0.0273	-0.0278	-0.0271
	(-2.12)	(-2.17)	(-1.22)	(-1.25)	(-1.22)
STD(EPS Forecast)	-0.323*	-0.321	-0.380	-0.392	-0.396
	(-1.65)	(-1.64)	(-1.46)	(-1.51)	(-1.52)
Pct Sales Supplier	-0.00211	0.00617	0.0532	0.0492	0.0469
	(-0.02)	(0.06)	(0.40)	(0.37)	(0.36)
Pct COGS Customer	-0.0604	-0.0126	-0.887	-1.003	-1.045
	(-0.08)	(-0.02)	(-1.13)	(-1.29)	(-1.35)
Intercept	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair	Pair
N	110969	110969	70747	70747	70747
R-sq	0.240	0.240	0.273	0.273	0.273
adj. R-sq	0.158	0.158	0.190	0.190	0.190

Panel C: Market-Adjusted Speed Measure

	Dependent Variable: Market-Adjusted Speed Measure				
	(1)	(2)	(3)	(4)	(5)
Analyst Dual Cov	**0.00400*** **				**0.00497** **
	(2.65)				**(2.34)**
Broker Dual Cov		**0.00156** **		**0.00156***	
		(2.10)		**(1.67)**	
Inst Cross Hold			**0.00615*** **	**0.00616*** **	**0.00610*** **
			(4.06)	**(4.06)**	**(4.02)**
ln(1+ #Analysts Customer)	-0.000495	-0.000364	-0.000417	-0.000629	-0.000934
	(-0.18)	(-0.13)	(-0.12)	(-0.18)	(-0.27)
ln(1+ #Analysts Supplier)	0.000744	0.000205	0.00163	-0.000408	0.0000734
	(0.33)	(0.08)	(0.51)	(-0.12)	(0.02)
ln(MV Customer)	0.00405*	0.00401*	0.00476	0.00479	0.00483
	(1.77)	(1.75)	(1.58)	(1.60)	(1.61)
ln(MV Supplier)	0.00446***	0.00429***	0.00554***	0.00511***	0.00526***
	(2.99)	(2.88)	(2.81)	(2.60)	(2.68)
abs(SUE)	-0.0145	-0.00995	0.0628	0.0599	0.0504
	(-0.10)	(-0.07)	(0.34)	(0.33)	(0.28)
SUE Neg (y/n)	-0.00395**	-0.00401**	-0.00565**	-0.00569***	-0.00564**
	(-2.47)	(-2.51)	(-2.56)	(-2.58)	(-2.56)
STD(EPS Forecast)	-0.0107	-0.0109	0.0151	0.0138	0.0132
	(-0.48)	(-0.49)	(0.48)	(0.44)	(0.42)
Pct Sales Supplier	0.00880	0.00975	0.00860	0.00836	0.00781
	(0.87)	(0.97)	(0.60)	(0.59)	(0.55)
Pct COGS Customer	-0.0346	-0.0305	0.0832	0.0671	0.0629
	(-0.34)	(-0.30)	(0.66)	(0.53)	(0.50)
Intercept	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair	Pair
N	110549	110549	70877	70877	70877
R-sq	0.173	0.173	0.190	0.190	0.190
adj. R-sq	0.083	0.083	0.097	0.097	0.097

Table 3. Measures of Flu Incidence in 10 US CDC Regions

This table presents the summary statistics of two measures for the flu incidence across all 10 US HHS regions as used by the Center for Disease Control and Prevention (CDC) between 1997 and 2014. The first measure of flu incidence reported in in Panel A is 'the percentage of patient visits with influenza-like-illness symptoms' collected by the CDC. The second flu incidence measure, as reported in Panel B, is the 'percentage of flu tests with positive results' collected by WHO/NREVSS Laboratories.

Panel A: Patient Visits with Influenza-like-Illness Symptoms (%)

CDC Region	N	Mean	SD	Min	p25	p50	p75	Max
#01 (New England)	841	0.99	1.04	0.02	0.43	0.70	1.19	9.82
#02 (North East)	841	1.85	1.49	0.00	0.97	1.52	2.24	13.42
#03 (Mid-Atlantic)	841	1.96	1.38	0.15	1.09	1.56	2.32	12.30
#04 (South East)	841	1.75	1.31	0.14	0.92	1.30	2.19	8.78
#05 (Mid-West North)	841	1.64	1.28	0.11	0.87	1.23	1.98	10.43
#06 (South)	841	2.33	1.94	0.00	1.13	1.80	3.00	13.18
#07 (Mid-West South)	841	1.34	1.56	0.00	0.47	0.82	1.56	12.18
#08 (Mountains)	841	1.16	1.16	0.00	0.48	0.85	1.40	10.16
#09 (Pacific South)	841	1.97	1.16	0.39	1.13	1.68	2.52	6.85
#10 (Pacific North)	841	1.68	1.38	0.00	0.73	1.34	2.17	9.61
Total	8410	1.67	1.44	0.00	0.76	1.27	2.09	13.42

Panel B: Flu Tests Positive (%)

CDC Region	N	Mean	SD	Min	p25	p50	p75	Max
#01 (New England)	871	8.82	11.61	0.00	0.00	2.70	15.52	53.05
#02 (North East)	885	6.86	9.00	0.00	0.17	2.60	11.21	53.53
#03 (Mid-Atlantic)	877	8.68	12.51	0.00	0.00	1.87	14.07	61.79
#04 (South East)	872	8.61	9.04	0.00	1.37	5.27	13.84	48.15
#05 (Mid-West North)	891	9.52	12.60	0.00	0.37	2.85	15.77	57.67
#06 (South)	872	7.81	10.11	0.00	0.63	2.48	12.10	43.90
#07 (Mid-West South)	889	6.25	9.47	0.00	0.00	1.15	9.55	50.05
#08 (Mountains)	884	7.64	9.86	0.00	0.00	2.47	12.79	50.38
#09 (Pacific South)	885	9.61	10.53	0.00	1.57	5.81	14.34	55.27
#10 (Pacific North)	874	8.88	10.35	0.00	0.77	4.73	13.95	48.31
Total	8800	8.27	10.63	0.00	0.33	3.09	13.23	61.79

Table 4. Flu Incidence in New York City (NYC) Area, Analyst/Broker Dual-Coverage and the Speed of Information Diffusion

This table presents results of the interaction effect between flu incidence in the New York City (NYC) area and analyst/broker dual-coverage on the speed of information diffusion along supply chains. Results based on analyst dual-coverage are reported in Panel A and results based on broker dual-coverage are reported in Panel B. *Flu in NYC 1* represents the ILI measure, the percentage of patient visits to medical care providers for 'influenza like illness symptoms' as reported by the Center for Disease Control (CDC) for the New York/New Jersey area. *Flu in NYC 2* is the 'percentage of flu tests with positive results' in the New York/New Jersey are collected by WHO/NREVSS laboratories. We include controls for firm size and analyst coverage of both customer and supplier, earnings announcement specific controls such as the absolute value of the earnings surprise, analyst forecast dispersion, an indicator for a negative SUE, as well as relationship specific controls including relationship strength from the customer and supplier perspective in each regression. Detailed definitions of dependent and independent variables are provided in Appendix I. We include relationship, year and quarter fixed effects in all specifications. *t*-statistics, listed in parentheses, are calculated based on standard errors clustered at the relationship-level in each model. $*$, $**$ and $***$ indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Analyst Dual Coverage and the Flu in NYC

	Dependent Variable:			
	Unadjusted Speed Measure		Market-Adjusted Speed Measure	
	(1)	(2)	(3)	(4)
Analyst Dual Cov	0.00681***	0.00549**	0.00574***	0.00554***
	(2.85)	(2.37)	(3.03)	(3.11)
NYC Flu 1	-0.00283***		-0.000586	
	(-3.47)		(-0.78)	
Analyst Dual Cov * NYC Flu 1	**-0.00133*** **		**-0.00111*** **	
	(-3.65)		**(-3.38)**	
NYC Flu 2		-0.00110***		0.0000473
		(-6.59)		(0.32)
Analyst Dual Cov * NYC Flu 2		**-0.000149*** **		**-0.000229*** **
		(-2.60)		**(-4.22)**
ln(1+ #Analysts Customer)	0.00138	0.00186	0.00517*	0.00487*
	(0.36)	(0.49)	(1.73)	(1.67)
ln(1+ #Analysts Supplier)	0.0220***	0.0213***	0.00814***	0.00751**
	(6.09)	(6.07)	(2.70)	(2.55)
ln(MV Customer)	0.00417	0.00494	-0.000140	-0.000161
	(1.20)	(1.46)	(-0.05)	(-0.06)
ln(MV Supplier)	0.0165***	0.0181***	0.00442**	0.00433**
	(6.91)	(7.71)	(2.32)	(2.33)
abs(SUE)	0.251	0.157	-0.187	-0.231
	(1.15)	(0.74)	(-1.01)	(-1.28)
SUE Neg (y/n)	-0.00423*	-0.00488**	-0.00480**	-0.00427**
	(-1.69)	(-2.00)	(-2.27)	(-2.04)
STD(EPS Forecast)	-0.0384	-0.0349	0.0635*	0.0671**
	(-1.00)	(-0.92)	(1.95)	(2.09)
Pct Sales Supplier	-0.00763	-0.00507	0.00580	0.00935
	(-0.44)	(-0.30)	(0.40)	(0.65)
Pct COGS Customer	0.157	0.143	0.149	0.146
	(0.85)	(0.78)	(0.86)	(0.85)
Intercept	Yes	Yes	Yes	Yes
Firm & Relationship Controls	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair
N	70986	73677	70986	73677
R-sq	0.315	0.312	0.152	0.149
adj. R-sq	0.243	0.243	0.063	0.063

Panel B: Broker Dual Coverage and the Flu in NYC

	Dependent Variable:			
	Unadjusted Speed Measure		Market-adjusted Speed Measure	
	(1)	(2)	(3)	(4)
Broker Dual Cov	0.00343***	0.00259**	0.00248***	0.00198**
	(3.22)	(2.52)	(2.77)	(2.39)
NYC Flu 1	-0.00210**		-0.0000904	
	(-2.43)		(-0.12)	
Broker Dual Cov * NYC Flu 1	**-0.000654*** **		**-0.000505*** **	
	(-4.01)		**(-3.42)**	
NYC Flu 2		-0.00107***		0.0000256
		(-6.01)		(0.16)
Broker Dual Cov * NYC Flu 2		**-0.0000425***		**-0.0000461** **
		(-1.67)		**(-2.10)**
ln(1+ #Analysts Customer)	0.00140	0.00201	0.00524*	0.00504*
	(0.37)	(0.53)	(1.75)	(1.72)
ln(1+ #Analysts Supplier)	0.0204***	0.0197***	0.00723**	0.00658**
	(5.37)	(5.35)	(2.29)	(2.13)
ln(MV Customer)	0.00418	0.00495	-0.000155	-0.000180
	(1.21)	(1.46)	(-0.06)	(-0.07)
ln(MV Supplier)	0.0162***	0.0177***	0.00424**	0.00408**
	(6.73)	(7.50)	(2.21)	(2.18)
abs(SUE)	0.261	0.165	-0.177	-0.223
	(1.19)	(0.77)	(-0.95)	(-1.24)
SUE Neg (y/n)	-0.00438*	-0.00498**	-0.00492**	-0.00435**
	(-1.75)	(-2.04)	(-2.33)	(-2.08)
STD(EPS Forecast)	-0.0416	-0.0363	0.0611*	0.0658**
	(-1.08)	(-0.95)	(1.87)	(2.04)
Pct Sales Supplier	-0.00718	-0.00461	0.00617	0.00970
	(-0.42)	(-0.27)	(0.42)	(0.68)
Pct COGS Customer	0.141	0.132	0.141	0.144
	(0.77)	(0.72)	(0.82)	(0.85)
Intercept	Yes	Yes	Yes	Yes
Firm & Relationship Controls	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair
N	70986	73677	70986	73677
R-sq	0.315	0.312	0.152	0.148
adj. R-sq	0.243	0.243	0.063	0.062

Table 5 Local Flu Activity, Institutional Cross-Holding, and the Speed of Information Diffusion

This table presents results of interaction effect between local flu incidence and institutional cross-holdings on the speed of information diffusion along supply chains. Locations of institutional investors are obtained from the FactSet LionShares Ownership database. For each cross-holding institutional investor we determine to what extent their current location is affected by the flu in any given week relying on the Center for Disease Control's (CDC) 'influenza like illness (ILI)' measure (*Cr. Own Flu 1)* and WHO/NREVSS's 'percentage of flu tests with positive results' (*Cr. Own Flu 2*) as our two measures of local flu incidence. Detailed definitions of dependent and independent variables are provided in Appendix I. We include relationship, year and quarter fixed effects in all specifications. *t*-statistics, provided in parentheses, are calculated based on standard errors clustered at the relationship-level in each model. $*$, $**$ and $***$ indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:					
	Unadjusted Speed Measure		Market-Adjusted Speed Measure			
	(1)	(2)	(3)	(4)	(5)	(6)
Cross Own	0.00769***	0.00760***	0.00826***	0.00716***	0.00643***	0.00563***
	(4.03)	(4.41)	(4.49)	(4.14)	(3.44)	(3.27)
Cross Own Location Flu 1	0.00135		0.00288			
	(0.70)		(1.60)			
Cr. Own * Cr. Own Flu 1	**-0.00289*** **		**-0.00258*** **			
	(-3.31)		**(-3.24)**			
Cross Own Location Flu 1		-0.000497*		0.000270		
		(-1.93)		(1.16)		
Cr. Own * Cr. Own Flu 2		**-0.000336*** **		**-0.000304*** **		
		(-2.96)		**(-3.05)**		
NYC Flu 1					-0.00193**	
					(-2.35)	
Cross Own * NYC Flu 1					**-0.000565**	
					(-1.15)	
NYC Flu 2						-0.00103***
						(-6.32)
Cross Own * NYC Flu 1						**-0.0000500**
						(-0.63)
ln(1+ #Analysts Customer)	0.000727	0.00155	-0.00243	-0.00278	-0.00234	-0.00277
	(0.19)	(0.40)	(-0.64)	(-0.75)	(-0.62)	(-0.74)
ln(1+ #Analysts Supplier)	0.0229***	0.0223***	0.00346	0.00191	0.00360	0.00205
	(6.37)	(6.36)	(1.00)	(0.57)	(1.05)	(0.61)
ln(MV Customer)	0.00381	0.00507	0.00334	0.00344	0.00336	0.00319
	(1.09)	(1.49)	(1.02)	(1.07)	(1.03)	(0.99)
ln(MV Supplier)	0.0160***	0.0179***	0.00378*	0.00513**	0.00384*	0.00503**
	(6.71)	(7.61)	(1.70)	(2.35)	(1.73)	(2.31)
abs(SUE)	0.277	0.192	0.419*	0.320	0.424*	0.298
	(1.27)	(0.90)	(1.93)	(1.51)	(1.96)	(1.41)
SUE Neg (y/n)	-0.00355	-0.00415*	-0.00419*	-0.00509**	-0.00436*	-0.00557**
	(-1.42)	(-1.69)	(-1.76)	(-2.18)	(-1.83)	(-2.38)
STD(EPS Forecast)	-0.0388	-0.0352	0.0356	0.0418	0.0354	0.0419
	(-1.00)	(-0.93)	(1.01)	(1.21)	(1.00)	(1.21)
Pct Sales Supplier	-0.00786	-0.00528	-0.0131	-0.00573	-0.0129	-0.00556
	(-0.46)	(-0.31)	(-0.82)	(-0.37)	(-0.81)	(-0.35)
Pct COGS Customer	0.157	0.149	-0.0461	-0.0330	-0.0426	-0.0312
	(0.85)	(0.81)	(-0.28)	(-0.21)	(-0.26)	(-0.20)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair	Pair	Pair
N	70575	73231	70575	73231	70575	73231
R-sq	0.316	0.314	0.174	0.171	0.174	0.171
adj. R-sq	0.243	0.244	0.087	0.087	0.087	0.087

Table 6: Speed of Supply Chain Information Diffusion and Customer Momentum Strategies

This table reports calendar-time portfolio returns and alphas. At the beginning of each calendar month, stocks are first sorted by a speed measure, i.e., either market capitalization or the speed of information diffusion measure into three equal groups. In each sub-group based on size or the speed of information diffusion, stocks are then sorted into five quintile portfolios based on the (portfolio) returns of its principal customers at the end of the previous month. All stocks are equally weighted within a given portfolio and the portfolios are reconstituted every calendar month. This table includes all available stocks with stock price greater than $5 between January 1980 and December 2013. We report results based on both raw portfolio returns (Panel A) and alphas (Panel B) after adjustments for the market factor, the Fama-French (1993) size and value factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Returns and alphas are reported at the monthly frequency. The *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-weighted Portfolio Returns

	Market Capitalization			Speed Measure		
Groups	Small	Medium	Large	Slow	Medium	Fast
Q1 (Low Customer Return)	0.488	0.398	0.835	0.286	0.568	0.886
Q2	0.812	0.732	0.891	0.879	0.781	0.945
Q3	1.024	0.909	1.269	0.998	0.973	1.132
Q4	1.279	1.240	0.964	1.209	1.156	1.104
Q5 (High Customer Return)	1.455	1.204	1.315	1.483	1.253	1.162
Q5-Q1	0.967***	0.806***	0.479**	1.197***	0.685***	0.276
t-stat	(4.17)	(3.37)	(1.98)	(5.11)	(2.80)	(1.36)

Panel B: Five-Factor Alpha

	Market Capitalization			Our Speed Measure		
Groups	Small	Medium	Large	Slow	Medium	Fast
Q1 (Low Customer Return)	-0.556***	-0.599***	-0.237	-0.797	-0.533	-0.160
t-stat	(-3.13)	(-3.21)	(-1.20)	(-3.54)	(-2.84)	(-1.33)
Q2	-0.304*	-0.267	-0.148	-0.145	-0.290	-0.122
t-stat	(-1.93)	(-1.64)	(-0.88)	(-0.79)	(-1.61)	(-0.75)
Q3	-0.027	-0.209	0.223	-0.074	-0.162	0.130
t-stat	(-0.17	(-1.37)	(1.37)	(-0.42)	(-0.94)	(0.89)
Q4	0.247	0.151	-0.107	0.166	0.041	0.049
t-stat	(1.46)	(0.89)	(-0.61)	(0.91)	(0.23)	(0.29)
Q5 (High Customer Return)	0.382**	0.141	0.329*	0.459	0.142	0.280
t-stat	(2.12)	(0.81)	(1.68)	(2.08)	(0.77)	(1.08)
Q5-Q1	0.938***	0.740***	0.566**	1.256***	0.675***	0.441
t-stat	(3.87)	(2.98)	(2.24)	(4.34)	(2.62)	(1.42)

Table 7: Speed of Information Diffusion and the Price-Investment Feedback Effect

This table summarizes panel regressions of quarterly change in assets (Panel A) and capital expenditure (Panel B) of suppliers on our variables of interest, including the lagged Tobin's Q of the customer firm (*Q Customer(t-1)*), the lagged Tobin's Q of the supplier firm itself (*Q Supplier (t-1)*), the speed of information diffusion from customer to supplier around the customer's earnings announcement (*Speed (t-1))*), the interaction term between lagged Tobin's Q of the customer and the speed measure, and the interaction term between the lagged Tobin's Q of the supplier and the speed measure. In addition to these key independent variables, we also include the following lagged firm characteristics of suppliers as control variables: book leverage (*Leverage Supplier (t-1)*), cash holdings (Cash Holding Supplier (t-1)), cash flow (CF Supplier (t-1)) as well as their interactions with Supplier-Q, and inversed asset size (*Asset Invest Supplier (t-1)*), return on assets (*ROA Supplier (t-1)*) and sales turnover (*Sales Turnover Supplier(t-1)*). All accounting related variables are winsorized at the 1% level. We incorporate relationship and year-quarter fixed effects in all specifications. *t*-statistics computed based on standard errors clustered at the relationship-level in each model are listed in parentheses. $*$, $**$ and $***$ indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Quarterly Change in Asset Size of Suppliers

	Dependent Variable: Quarterly Change in Assets (t)			
	(1)	(2)	(3)	(4)
Q Supplier (t-1)	0.0623***	0.0604***	0.0623***	0.0602***
	(21.91)	(21.19)	(21.92)	(21.08)
Q Customer (t-1)	0.00822***	0.00811***	0.00964***	0.0102***
	(4.10)	(4.04)	(4.63)	(4.90)
Speed (t-1)		-0.0305**	0.0180**	-0.00890
		(-2.08)	(2.23)	(-0.60)
Q Supplier (t-1) * Speed (t-1)		**0.0102****		**0.0119****
		(1.97)		**(2.05)**
Q Customer (t-1) * Speed (t-1)			**-0.00717****	**-0.0105*****
			(-2.30)	**(-3.24)**
Leverage Supplier (t-1)	0.000528	0.000544	0.000524	0.000539
	(1.39)	(1.43)	(1.37)	(1.41)
*Q Sup. (t-1) * Lev. Sup. (t-1)*	-0.0000289	-0.0000397	-0.0000260	-0.0000373
	(-0.19)	(-0.26)	(-0.17)	(-0.25)
Cash Holdings Supplier (t-1)	-0.0417	-0.0414	-0.0417	-0.0413
	(-1.55)	(-1.53)	(-1.55)	(-1.53)
*Q Sup. (t-1) * Cash Sup. (t-1)*	-0.0128*	-0.0129*	-0.0128*	-0.0129*
	(-1.86)	(-1.88)	(-1.86)	(-1.88)
Cash Flow Supplier (t-1)	0.0210	0.0222	0.0209	0.0223
	(0.33)	(0.35)	(0.33)	(0.35)
*Q Sup. (t-1) * CF Sup. (t-1)*	-0.0322	-0.0326	-0.0321	-0.0326
	(-1.43)	(-1.44)	(-1.43)	(-1.45)
Assets Inverse Supplier (t-1)	2.040***	2.041***	2.040***	2.040***
	(8.46)	(8.47)	(8.46)	(8.47)
ROA Supplier (t-1)	-0.00192	-0.00220	-0.00185	-0.00215
	(-0.12)	(-0.13)	(-0.11)	(-0.13)
Sales Turnover Supplier (t-1)	0.115**	0.115**	0.115**	0.115**
	(2.43)	(2.43)	(2.43)	(2.43)
Intercept	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair
N	105117	105117	105117	105117
R-sq	0.240	0.240	0.240	0.240
adj. R-sq	0.154	0.154	0.154	0.155

Panel B: Quarterly Capital Expenditure of Suppliers

	Dependent Variable: Quarterly CapEx (t)			
	(1)	(2)	(3)	(4)
Q Supplier (t-1)	0.0106***	0.0102***	0.0106***	0.0102***
	(12.90)	(12.87)	(12.89)	(12.88)
Q Customer (t-1)	0.000843**	0.000829*	0.000790*	0.000853**
	(1.97)	(1.94)	(1.88)	(2.03)
Speed (t-1)		-0.00677***	0.000535	-0.00652***
		(-3.17)	(0.35)	(-2.86)
Q Supplier (t-1) * Speed (t-1)		**0.00298*** **		**0.00300*** **
		(3.82)		**(3.75)**
Q Customer (t-1) * Speed (t-1)			**0.000264**	**-0.000122**
			(0.56)	**(-0.25)**
Leverage Supplier (t-1)	-5.23e-05	-3.24e-05	-5.08e-05	-3.26e-05
	(-0.55)	(-0.34)	(-0.54)	(-0.34)
*Q Sup. (t-1) * Lev. Sup. (t-1)*	5.02e-05	3.68e-05	4.84e-05	3.69e-05
	(1.11)	(0.80)	(1.07)	(0.80)
Cash Holdings Supplier (t-1)	0.0237***	0.0235***	0.0237***	0.0235***
	(5.84)	(5.82)	(5.84)	(5.82)
*Q Sup. (t-1) * Cash Sup. (t-1)*	-0.00899***	-0.00897***	-0.00899***	-0.00897***
	(-9.60)	(-9.60)	(-9.60)	(-9.60)
Cash Flow Supplier (t-1)	-0.0179***	-0.0179***	-0.0179***	-0.0179***
	(-3.22)	(-3.24)	(-3.22)	(-3.24)
*Q Sup. (t-1) * CF Sup. (t-1)*	0.000587	0.000587	0.000582	0.000588
	(0.55)	(0.55)	(0.54)	(0.55)
Assets Inverse Supplier (t-1)	0.0229	0.0228	0.0228	0.0228
	(1.03)	(1.03)	(1.03)	(1.03)
ROA Supplier (t-1)	0.00487*	0.00482*	0.00488*	0.00482*
	(1.73)	(1.72)	(1.74)	(1.72)
Sales Turnover Supplier (t-1)	0.0112***	0.0112***	0.0112***	0.0112***
	(3.19)	(3.20)	(3.20)	(3.20)
Intercept	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Clustered SE	Pair	Pair	Pair	Pair
N	102241	102241	102241	102241
R-sq	0.630	0.630	0.630	0.630
adj. R-sq	0.587	0.588	0.587	0.588