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

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Abstract

We develop a new measure for the speed of firm-level information diffusion in stock prices and study its determinants and implications. Using local flu epidemics as exogenous attention shocks, we show that inattention from dual-covering analysts and cross-holding institutions decreases the speed of information diffusion from customers to suppliers. Supply-chain information diffusion matters for investors and firms: we document that information diffusion speed drives customer momentum strategies, affects the price feedback effect for corporate investment decisions, and enhances supply-chain coordination. Our findings demonstrate that attention from key information intermediaries affects information efficiency with important implications for real economic outcomes.

Keywords: Information Diffusion; Limited Attention; Supply Chains; Firm Investment

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1 Introduction

In the presence of limited attention and market frictions, information diffusion between economically linked firms can be slow. As a result, past returns of one firm may predict the returns of related firms. Consistent with this notion, previous studies document lead-lag effects of stock returns between firms in the same industry (Moskowitz and Grinblatt, 1999; Hou, 2007), firms in supply chain relationships (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), single- and multi-segment firms in the same industry (Cohen and Lou, 2012), strategic alliances (Cao, Chordia, and Lin, 2016), and firms with similar technologies (Lee, Sun, Wang, and Zhang, 2019) and headquarter locations (Parsons, Sabbatucci, and Titman, 2020).

The evidence presented in these papers suggests that when firms are closely connected to each other information efficiency is largely determined by how quickly and accurately stock prices incorporate relevant information from related firms. However, while the literature primarily focuses on the profitability of portfolio-level trading strategies, few attempt to quantify and study the speed of information diffusion at the firm-level. This is important since information efficiency is a key feature of capital markets and has important implications for the allocative efficiency of real economic outcomes.[1]

In this paper, we develop a firm-level measure of the speed of information diffusion between economically linked firms, study its determinants, and examine how the speed of information diffusion affects real corporate decisions related to business interaction and coordination between economically linked firms. Specifically, we study two research questions: first, how does attention from key market participants, such as analysts and institutional investors, affect the speed of information diffusion from corporate customers to their suppliers, and second, what are the implications of slow information diffusion in stock returns for capital investment and supply-chain coordination?

[1]For a summary of the literature see for example Bond, Edmans, and Goldstein (2012). Evidence on the effect of stock price efficiency for real economic outcomes include CEO compensation (Kang and Liu, 2008), monitoring (Ferreira, Ferreira, and Raposo, 2011) and blockholder incentives (Faure-Grimaud and Gromb, 2004; Edmans, 2009), equity issuance (Grullon, Michenaud, and Weston, 2015), takeovers (Edmans, Goldstein, and Jiang, 2012), and investments (Chen, Goldstein, and Jiang, 2007).

In addressing these questions we face two major challenges. First, cross-firm return predictability can be driven not only by slow diffusion of relevant information, but by other confounding effects such as spillovers of investor sentiment across firms, i.e. sentiment contagion, (Baker, Wurgler, and Yuan, 2012) and common trends in stock return autocorrelations, i.e. commonality in own-momentum (Burt and Hrdlicka, 2020). In the same vein, Griffin, Kelly, and Nardari (2010) show that standard measures of information diffusion based on stock returns can produce misleading results when stock returns are dominated by noise in emerging markets.

We address this first challenge by constructing a measure of the speed of information diffusion in a supply-chain setting. Specifically, we estimate the degree to which return residuals of dependent suppliers reflect past return residuals of their principal customers. Our approach has several key advantages. Purchases by principal customers typically represent a large proportion of the total sales of their dependent suppliers but only a small proportion in customers' cost of goods sold. This strong, asymmetric economic link allows us to identify the type (i.e. supply-chain-related information) and the direction of information diffusion (i.e., from customers to suppliers), which is important for studying the implications of information efficiency for real economic outcomes.[2] Further, we calculate our speed measure in the period around earnings announcements of the customer firms, allowing us to focus on regularly occurring, scheduled events that contain important information for supplier stock returns.[3] Under this setting, information is likely to dominate noise in stock prices, hence addressing concerns that information efficiency proxies can be spurious when stock returns are dominated by sentiment contagion or noise. Last, by focusing on narrow windows around customer earnings announcements, we can alleviate concerns that long-term commonality in momentum is the main driver of lead-lag effects.

[2] Previous studies estimating delays in information diffusion have mainly focused on the diffusion of market-level information (Hou and Moskowitz, 2005; Hou, 2007; Bae, Ozoguz, Tan, and Wirjanto, 2012; Boehmer and Wu, 2013).

[3] Given that customer earnings announcements are well-publicized, we believe that slow diffusion around these events can serve as a useful, albeit upward biased, proxy for slow diffusion of other customer information, much of which is less well-publicized.

Second, the attention of market participants and the flow of information are jointly determined in equilibrium. On one hand, analysts that simultaneously cover economically linked firms (i.e., analyst dual-coverage) may expedite information diffusion in financial markets by collecting, analyzing, and disseminating information, thus attenuating cross-firm return predictability. On the other hand, as documented in a recent paper by Ali and Hirshleifer (2020), analyst dual-coverage may signal strong fundamental linkages between firms when dual-coverage is not assigned randomly. In this case, relative to pairs of randomly selected firms, news about firms with shared analysts may contain more relevant information and are more likely to generate lead-lag effects in stock returns. Therefore, we would not be able to derive meaningful economic interpretations based only on the correlation of (co)attention by key market participants and the speed of information diffusion.

To address this concern, we rely on an exogenous shock to the attention of key market participants: regional flu epidemics in the US. Following Dong and Heo (2019), 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 temporary reduction in attention and information processing capabilities of analysts and institutional investors. In addition to the analysts and investors themselves, flu that affects their family members, colleagues, or support staff may also sap attention and slow information diffusion, even if the institutional investors and analysts themselves are not directly affected. Essentially, this approach allows us to hold the fundamental linkages between firms constant and randomly vary the information processing abilities of dual-covering analysts and cross-holding institutional investors based on their geographic locations.

We use data from the Center for Disease Control (CDC) on the "percentage of flu tests with positive results" to identify local peaks of flu exposure as weeks in which the regional flu measure exceeds a critical threshold. Our first set of tests focuses on flu epidemics in New York, the workplace and residence of most financial analysts. We show that supply-chain information generally diffuses more slowly when the New York region is affected by a serious flu epidemic. More importantly, consistent with the role of dual-covering analysts and brokers in facilitating supply-chain information diffusion, we find that this effect is much stronger when affected analysts and brokers simultaneously cover customers and suppliers. In the second set of tests, we identify detailed location information for a subset of financial analysts and institutional investors. For the same supply-chain relationship, the speed of information diffusion declines when dual-covering analysts or cross-holding institutional investors are located in a region affected by a serious local flu epidemic. Taken together, these findings provide causal evidence that the attention of key market participants to supply-chain relationships increases the speed of information diffusion along the supply chain.

We next investigate how practitioners may use our speed measure and how the speed of information diffusion affects real economic outcomes. With respect to investors, we find that our measure can be used to generate a more profitable customer momentum strategy (Cohen and Frazzini, 2008) by identifying relationship-pairs where information diffuses more slowly from customers to suppliers. Consistent with our measure parsimoniously capturing the various frictions in the price formation process, we find that the speed of supply-chain information diffusion does better at identifying profitable customer momentum than other individual proxies for supply-chain diffusion speed.

With respect to corporate managers, we find that the speed of supply-chain information diffusion positively affects the sensitivity of supplier investment to its own stock price and negatively affects supplier investment sensitivity to its customer's stock price. This is consistent with the notion that, when the speed of supply-chain information diffusion is faster, supplier stock prices contain more supplier-relevant customer information. In this case, when supplier managers identify useful information in stock prices to guide their investment decisions, they rely more on their own stock prices. Alternatively, when information diffusion speed is slower, supplier stock prices are less efficient with respect to supply-chain information and supplier managers have to rely more on customer stock prices to guide their investment decisions. Overall, our findings indicate that quantifying the speed of information diffusion across economically linked firms can help investors 'fine-tune' trading strategies and help managers optimize corporate investment decisions.

Finally, we argue that information diffusion through stock prices provides a public information sharing channel that facilitates the coordination of investments between customers and suppliers. Consistent with this conjecture, we find a positive correlation between information diffusion speed and investment coordination between supply chain partners, as captured by the co-movement of investments (as measured by the change in property, plant, and equipment and the scaled capital expenditure) between customers and suppliers. This positive correlation is robust after we control for the strength of supply-chain relationships, which may simultaneously affect information diffusion speed and investment coordination between supply chain partners. Further, we show that this public information sharing channel is orthogonal to other well-documented private information sharing channels, such as the geographical distance between customers and suppliers. However, we find a stronger correlation between the diffusion speed and investment coordination in the supply chain when private information sharing is weaker. This result suggests that information sharing through public (e.g., through stock prices) and private channels (e.g., through private communications) are substitutes in facilitating investment coordination along the supply chain.

Our paper is most closely related to the literature on the limited attention of investors. Psychological constraints in processing capability and cognitive resources lead to limited attention (Kahneman, 1973), which generates underreaction to information (e.g., Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009) and slow information diffusion across economically linked firms (e.g., Hong, Torous, and Valkanov, 2007 and papers mentioned in the first paragraph of our introduction). Recent studies suggest that co-attention of professional market participants, such as analyst dual-coverage (Guan, Wong, and Zhang, 2015; Ali and Hirshleifer, 2020) and institutional cross-holding (Cohen and Frazzini, 2008; Cen, Danesh, Ornthanalai, and Zhao, 2019) can mitigate limited attention and facilitate information diffusion between economically linked firms. We contribute to this literature by building a quantitative and causal link between the co-attention of professional market participants, i.e., analysts and institutional investors, and the speed of information diffusion in a unique research setting where the type of information and direction of information diffusion can be identified.

Our paper is also related to the literature on information sharing between customers and suppliers and its real economic consequences on supply chain coordination. Previous studies show that information sharing between supply chain partners is important to mitigate hold-up problems, induce relationship-specific investments, and generate synergies in supply-chain coordination, such as technology innovations (Chu, Tian, and Wang, 2019; Liang, Williams, and Xiao, 2020) and tax strategies (Cen, Maydew, Zhang, and Zuo, 2017). This information sharing can be carried out strategically through public information channels such as earnings announcement (Raman and Shahrur, 2008) or private information sharing channels such as confidential communication in repeated daily interactions (Li and Zhang, 2008). We show that stock prices also serve as a public information sharing channel that can act as a substitute for private channels in facilitating coordination along the supply chain.

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 describe our speed measure. In Section 4, we show that investor (co)attention causally affects the speed of information diffusion based on an identification strategy of flu epidemics. We examine the implications of our speed measure for investors and managers in Section 5. Section 6 discusses the information diffusion through stock prices as a public information sharing channel for investment coordination between customers and suppliers. Section 7 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. Relying on the Compustat Segment Customer File, we follow the approach used in previous studies (e.g., Fee and Thomas, 2004; Cohen and Frazzini, 2008) to identify supplier-customer relationships by manually matching corporate customer names with their Compustat identifiers (i.e., GVKEYs) whenever possible. To measure the importance of a principal customer to its 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 obtain firm characteristics such as book value of total assets, total sales, market capitalization, cost of goods sold, and other items for both customers and suppliers from the Compustat Annual and Quarterly Files.

We exclude financial firms (SIC codes 6000 to 6999) and utilities (SIC codes 4000 to 4900) from this analysis since their investments are largely dependent on regulatory and capital requirements. To calculate the speed of supply-chain information diffusion, we require daily stock returns for both customers and suppliers around the customers' earnings announcements. We exclude relationship-quarters where either customers or suppliers do not have at least 25 daily return observations in the $[-10, 30]$ interval around the customer's earnings announcement date.

We obtain data on quarterly customer earnings announcements including announcement dates, actual earnings per share, mean and median earnings forecasts, forecast dispersion, and analyst coverage for both customers and suppliers for the 1983 to 2013 sample period from the I/B/E/S Unadjusted Summary File. In most of our tests, the variables from I/B/E/S

[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.

reflect the most recent forecast of each analyst before the earnings announcement date. Our sample selection criteria yield a final sample of 16,588 customer-supplier pairs (5,958 unique suppliers and 2,510 unique customers), providing a total of 107,156 observations, where the unit of observation is a supplier-customer relationship-quarter. Detailed variable definitions are provided in Appendix Table A.1.[5]

[Insert Table 1 here.]

Summary statistics describing principal customers, dependent suppliers, and customer-supplier relationships are presented in Panel A of Table 1. Consistent with previous studies in the supply-chain literature (e.g., Banerjee, Dasgupta, and Kim, 2008; Hertzel, Li, Officer, and Rodgers, 2008), principal customer firms in our sample are typically much larger than their dependent suppliers. The median customer firm is about 28 times larger than the median supplier firm in terms of the book value of total assets and about 25 times larger in terms of market capitalization. Not surprisingly, we also note that principal customers have higher analyst coverage with a median of 15 analysts compared to a median of only 2 analysts for dependent supplier firms. The ratio of sales to the principal customer over total sales reported by suppliers (i.e. *Pct of Supplier Sales*) is around 17.6%, on average, with an interquartile range of 9% to 21.0%. Although a principal customer is important to a supplier, the reverse is not typically the case. In our sample, suppliers only contribute a small fraction of their customers' total inputs; supplier sales to customers on average represent only 1.7% of the customers' cost of goods sold (COGS). The asymmetric mutual importance between principal customers and dependent suppliers allows us to pin down the direction of information diffusion in theory, i.e., from principal customers to dependent suppliers.

[5]We winsorize all accounting-related variables at the 5% level within the full Compustat universe to minimize the effect of outliers that are likely driven by reporting errors.

2.2 Dual-Coverage and Institutional Cross-Holding

We rely on the I/B/E/S Unadjusted Detail 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 supplier.[6] We similarly define broker dual-coverage if analysts from a brokerage firm simultaneously cover both the customer and the supplier.[7] From the Thomson Reuters Institutional Investors (13f) database we obtain information for institutional cross-holding for each relationship-quarter. We define cross-holding for a given supplier-customer pair, if at least 5% of outstanding shares of both firms are held by one active institutional investor and use the FactSet LionShares Ownership File to classify institutional investors 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.

As shown in Panel A of Table Table 1, 23.2% of the relationship-quarters in our sample are analyst dual-covered, 60.3% are broker dual-covered, and 40.2% have cross-holdings by at least one common active institutional investor. On average, each relationship-quarter is covered by 0.815 dual-covering analysts, 3.310 dual-covering brokerage firms, and 0.882 cross-holding institutional investors.

3 The Speed of Supply-Chain Information Diffusion

We develop a measure for the speed at which relevant customer information is reflected in supplier stock prices. Our measure is based on estimates of the speed of supply-chain

[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] For our main test specification, based on relationship-quarter observations, we assume that the analyst dual-coverage and broker dual-coverage status does not change within a calendar year.

information diffusion from customer returns to supplier returns around quarterly customer earnings announcements. We focus on customer earnings announcements for several reasons. First, they are important, recurring, firm-specific information events that can have significant implications for dependent suppliers.[8] In addition, stock price movements around customer earnings announcements are likely dominated by the impact of firm-specific and supply-chain relevant information instead of macroeconomic information, industry-wide information, market-wide sentiment or firm-specific idiosyncratic noise. Hence, we are able to obtain a more precise estimate of the speed of supply-chain information diffusion, mitigating concerns that delay measures can be unreliable when stock price movements are dominated by noise (e.g., Griffin et al., 2010). Finally, we note that because earnings announcements are well-publicized recurring events, our estimates likely yield a conservative proxy for diffusion speed when considered more broadly.

Summary statistics on customer 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 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 approximately twice as large as its mean value, suggesting a large dispersion of earnings surprises. This confirms that earnings announcements are major information events that significantly affect stock returns. Further, consistent with previous studies (e.g., Matsumoto, 2002; Bartov, Givoly, and Hayn, 2002), there are more positive earnings surprises (65%) than negative earnings surprises (35%) in our sample.

To measure the speed of supply-chain information diffusion we build upon the methodology first introduced by Mech (1993) in estimating the delay at which stock returns reflect information. This approach is formalized by Hou and Moskowitz (2005) and recently applied,

[8]For example, 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.

for example, by Boehmer and Wu (2013) and Bae et al. (2012).[9] Specifically, around each customer earnings announcement i, we estimate the following regression using customer and supplier market-adjusted (residual) returns over a 41-day trading period $[-10, 30]$, i.e., from 10 trading days before to 30 trading days after the earnings announcement date:[10]

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

where $R_{i,t}^{sup}$ denotes residuals of daily returns of suppliers after removing the market component; $R_{i,t}^{cus}$ denotes residuals of daily returns of customers[11]; and K denotes the number of lagged daily returns of customers that we incorporate into our estimation. Intuitively, if diffusion of firm-specific information from customers to suppliers is rapid, i.e., all customer earnings information is incorporated into supplier stock prices within one day, we expect that our estimate of β_0 will be positive and significantly different from zero while our estimates of β_k ($k = 1, 2, \ldots\ K$) 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 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:[12]

$$Speed = \frac{R^2_{\beta_k=0,\forall k\in[1,4]}}{R^2} \times 100. \tag{2}$$

[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 balance the goals of precisely estimating the model while limiting the effect of other confounding events or news before and after each earnings announcement.

[11] $R_{i,t}^{sup}$ and $R_{i,t}^{cus}$ are obtained as the difference between firm returns on day t and the contemporaneous expected returns from a market model, using an estimation window of 150 trading days with at least 120 non-missing observations, ending 15 trading days before day t. We use market residuals instead of raw returns in our analyses since we are focusing on the diffusion of customer firm-specific information.

[12] 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, similar to Boehmer and Wu (2013).

The larger *Speed*, 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. Therefore, a larger speed indicates a faster firm-specific information diffusion along the supply chain. For example, when all customer earnings information is reflected in the supplier's stock price on the customer's earnings announcement day, *Speed* should be close to 100.[13] Conversely, *Speed* 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 more slowly from customers to suppliers. As reported in Panel C of Table 1, the mean level of Speed is 23.332 with a standard deviation of 24.799. The average lag-one autocorrelation coefficient of *Speed* within each firm-pair in our sample is 0.685, suggesting that the speed of information diffusion measured around earnings announcements is fairly stable within a given supplier-customer relationship over time. Our speed measure has an economically intuitive interpretation. For example, its mean level suggests that, on average, 23.33% of all information diffusion from customers to suppliers over a one-week horizon is completed within the first day.

4 Determinants of Information Diffusion Speed

Previous studies (e.g., Cohen and Frazzini, 2008; Guan et al., 2015) have documented that supply-chain information diffusion is facilitated by market participants who simultaneously pay attention to both customers and suppliers. We begin by investigating whether our speed measure exhibits this key observation from prior literature. Specifically, in Section 4.1, we examine whether the existence of market participants that focus simultaneously on both customers and suppliers – dual-covering analysts, dual-covering brokers, and cross-holding institutional investors – is positively correlated with the speed of supply-chain information diffusion. The baseline results in Section 4.1 do not establish causality since dual-coverage and

[13]Note that our measure of information diffusion speed is a simple transformation of the Delay measure of Hou and Moskowitz (2005) and Hou (2007); i.e., $Speed = 100 - Delay$.

institutional cross-holding could be endogenously determined. We address this endogeneity issue in Section 4.2 using a natural experiment based on local flu peak activities as exogenous shocks to the attention of our key market participants.

4.1 Inattention and Information Diffusion: Baseline Results

Our baseline tests for the correlation between attention and diffusion speed are based on estimates of the following panel regression at the relationship-quarter level:

$$Speed_{i,j,t} = \alpha + \beta X_{i,j,t} + \delta_1 Z_{i,t} + \delta_2 Z_{j,t} + \delta_3 R_{i,j,t} + \delta_4 E_{j,t} + \gamma_i + \mu_j + \theta_t + \epsilon_{i,j,t} \tag{3}$$

where $Speed_{i,j,t}$ is our measure of the speed of supply-chain information diffusion from customer j to supplier i measured around the customer earnings announcement in quarter t; $Z_{i,t}$ and $Z_{j,t}$ are vectors of customer and supplier firm-level controls, including firm size and the numbers of analysts covering customers and suppliers. $R_{i,j,t}$ 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; $E_{j,t}$ is a vector of controls for characteristics of customer earnings announcements, including the magnitude and sign of earnings surprises as well as the pre-earnings-announcement analyst forecast dispersion; γ_i, μ_j, and θ_t are supplier, customer, and time (year-quarter) fixed effects, respectively. $X_{i,j,t}$ represents our main variables of interest, i.e., analyst dual-coverage, broker dual-coverage, or institutional cross-holding.

[Insert Table 2 here.]

The results, reported in Table 2, show that analyst dual-coverage, broker dual-coverage, and institutional cross-holding are positively correlated with the speed of supply-chain information diffusion. We carry out two sets of empirical tests based on Equation (3). In Panel A, $X_{i,j,t}$ are continuous variables capturing the number of dual-covering analysts, dual-covering brokers, and cross-holding institutional investors. The coefficient of *Analyst Dual Cov* in

Column (1) (0.884, statistically significant at the 1% level) suggests that a one standard deviation increase in *Analyst Dual Cov* is associated with an increase of 2.13 in the speed measure. This can be translated to an increase of 9.13% of the unconditional mean of the speed measure (23.332) in the full sample. The results in Columns (2) and (3) indicate that the number of dual-covering brokers and cross-holding institutional investors also exhibit a similar positive association with diffusion speed and, not surprisingly, the magnitude is smaller than that for the number of dual-covering analysts.[14] Columns (4) and (5) show that the number of dual-covering analysts and dual-covering brokers remains statistically and economically significance when the number of cross-holding institutional investors is included as an independent variable.[15] This finding suggests that analyst/broker dual-coverage and institutional cross-holdings contain incremental information in explaining diffusion speed and highlight the parsimonious nature of our speed measure in broadly capturing differing frictions that affect the speed with which customer information is reflected in supplier stock prices.

In Panel B, we replace the continuous variables for analyst and broker dual coverage and institutional cross-holding with the corresponding dummy variables. For example, *Dual Analyst* (0/1) is a dummy variable that is equal to 1 if a relationship is covered by at least one dual-covering analyst at time t. The results based on dummy variables (Panel B) are similar to those based on continuous variables (Panel A). The only noteworthy difference is that the coefficient of *Cross Owner* (0/1) is no longer statistically significant. This result is not surprising: the existence of one single cross-holding institutional investor is not sufficient to generate much impact on the speed of information diffusion along the supply chain.

We carry out several robustness tests for our baseline specification. Instead of using

[14]The coefficient estimates for *Num Dual Brokers* and *Num Cross Owners* indicate an increase in *Speed* of about 8% and 2% relative to the unconditional sample mean, respectively.

[15]These specifications are 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.

the speed measure computed with return residuals based on the CAPM model, we construct alternative speed measures based on raw returns as well as return residuals based on the Fama-French three-factor model. Results in Appendix Table A.2 suggest that the empirical patterns in the baseline specification are not affected irrespective of whether the speed measure is computed by raw returns or return residuals from Fama-French three-factor model.

4.2 Flu Epidemics and Market Participant Attention

While the results in the previous section are consistent with the hypothesis that market participants who simultaneously pay attention to both customers and suppliers increase the speed of supply-chain information diffusion, potential endogeneity concerns make it difficult to establish a causal link. For example, analysts may be more likely to dual-cover customer-supplier pairs that have closer economic links (Ali and Hirshleifer, 2020), 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. Further, unobserved common factors might affect both the speed of supply-chain information diffusion and the attention of market participants at the same time.

To address these concerns, we rely on 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.[16] Regional flu epidemics can have both direct and indirect effects on market participant attention. Direct effects are due to the fact that analysts and 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 attention and information processing capabilities of infected analysts and institutional investors. In addition to the analysts and institutional investors themselves, flu that affects family members or colleagues, e.g., team members and support staff, may also

[16] McTier, Tse, and Wald (2013) show that a high incidence of flu in the New York City area is associated with lower trading activity, volatility, and market liquidity. Dong and Heo (2019) find that flu in the New York area affects analysts' forecast behavior. We control for the implications of these findings in our analysis.

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 an exogenous shock to the attention of key market participants. 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 identify periods of peak flu activity, we rely on weekly healthcare and flu incidence records from 1997 to 2013, 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 provide flu data for 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 (2019) we use the "percentage of flu tests with positive results" (PP) from WHO/NREVSS from CDC as our main measure of flu epidemics. We define peak flu incidence as weeks in which the local "percentage of positive flu tests" (PP) exceeds 20%. For comparison, the median value and the 75th percentile of PP across all 10 CDC regions (New York) is 3.091 (2.597) and 13.233 (11.208), respectively.

The diagram in Figure 1 and summary statistics in Appendix Table A.3 show time-series and cross-sectional properties of our flu measure. We observe two clear patterns. First, although flu activity is typically clustered in winter and early spring, the severity, timing, and 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 and, therefore, are highly unpredictable. 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 geographic variations in our identification strategy.

4.2.1 Flu Epidemics and Conference Call Participation

We first provide evidence that local peak flu incidence materially affects analysts' activity and productivity by examining analyst participation in earnings conference calls. Specifically, we merge data from earnings conference call transcripts with sell-side analysts from I/B/E/S covering the firm hosting the conference call in the given period. For this test, we identify the geographic location of each analyst in the sample from FINRA's BrokerCheck platform, which provides detailed information on employment history and workplace location for each individual registered on FINRA. We retain all analysts which we can successfully match in I/B/E/S and FINRA and begin by examining whether local peak flu incidence affects an analyst's likelihood of attending the conference call. Table 3 reports the results of linear probability models, where the dependent variable, *Call Participation* (0/1), takes the value of one if the analyst covering the given firm participates in the firm's earning conference call, and zero otherwise.

[Insert Table 3 here.]

Earnings conference call participation of financial analysts (i.e., whether an analyst has an opportunity to ask questions in an earnings conference call) is jointly determined by 1) whether an analyst calls into the earnings conference call and 2) whether the managers or investor relation officers of the hosting firm takes questions from the analyst (Cen, Chen, Dasgupta, and Ragunathan, 2020). Including analyst-firm pair fixed effects in our regressions allows us to control for the connections between firms and analysts, which is the major determinant for hosting firms' willingness of taking questions from the analysts. Controlling for such incentives from the corporate side, Table 3 shows that local flu peak incidence reduces the likelihood of affected analysts' participation in earnings conference calls by 0.728

percentage points in the most stringent specification with analyst-firm and conference call fixed effects (Column 4). This can be compared to the unconditional likelihood for an analyst to participate conference calls hosted by a firm the analyst covers of 34.92%.

In the following sections, we carry out two sets of tests based on this flu setting. Our first set of tests focuses on peak flu activity in the New York Region to study the causal effect of analyst and broker dual-coverage on the speed of supply-chain information diffusion. Since most Wall Street financial analysts live and work in this geographic region, we conjecture that analysts are most likely affected by peak flu activity in the New York Region.[17] In the second set of tests, we exploit variation in the geographic location for a subset of analysts using data from FINRA's BrokerCheck (similar to the conference call tests presented above) and institutional investors from FactSet LionShares Ownership File. We examine how flu peak activities in the locations of dual-covering analysts and cross-holding institutional investors affect the speed of supply-chain information diffusion.

4.2.2 Flu Incidence in New York, Dual-Coverage, and Speed

To analyze the effect of flu epidemics on analysts and brokerage firms, we augment Equation (3) by interacting the analyst/broker dual-coverage variables with the New York area flu measures as follows:

$$\begin{aligned} Speed_{i,j,t} = \alpha + \beta_1 X_{i,j,t} + \beta_2 Peak\ Flu\ NY_t + \beta_3 (X_{i,j,t} \times\ Peak\ Flu\ NY_t) \\ + \delta_1 Z_{i,t} + \delta_2 Z_{j,t} + \delta_3 R_{i,j,t} + \delta_4 E_{i,t} + \gamma_i + \mu_j + \theta_t + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

where the control variables are the same as those in Equation (3), and $Peak\ Flu\ NY_t$ is a dummy variable that equals one when there is peak flu activity in the New York region during the week of the customer's earnings announcement. In this model, including customer, supplier, and time fixed effects subsumes all time-invariant determinants at the firm level

[17] 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.

as well as any time-trends and seasonality effects. β_2 then captures the average effect of flu epidemics in New York on the speed of information diffusion in the sample; β_3 is our main coefficient of interest, capturing how flu exposure affects the effect of dual-coverage and cross-ownership on the speed of information diffusion.

[Insert Table 4 here.]

Table 4 reports the estimates of 3. Similar to Table 2, X_{ijt} in Panel A are continuous variables capturing the number of dual-covering analysts, dual-covering brokers, and cross-holding institutional investors. Consistent with our findings in Table 2, the results in Column (1) 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. In Columns (1) and (2), the coefficient estimates for *Num Dual Analysts* and *Num Dual Brokers* (0.960 and 0.395) are comparable to those reported in Table 2. Further, consistent with McTier et al. (2013), we find a negative average effect of peak flu episodes in the NYC region on the speed of information diffusion, e.g., the coefficient of $Peak\ Flu\ NY_t$ is -0.373 in Column (1). This corresponds to a 1.60% decrease in the speed of information diffusion measure relative to the unconditional sample mean. Since New York is a global financial center hosting a large number of financial institutions and practitioners, it is not surprising that overall information efficiency is lower when the NYC area is adversely affected by flu incidence.

The key finding in Table 4 is that limited attention due to flu incidence in the New York City area affects the speed of supply-chain information diffusion *through* analyst dual-coverage. The coefficient of $Analyst\ Dual\ Cov \times\ Peak\ Flu\ NY_t$ in Column (1) (-0.311) implies that, while one additional dual-covering analyst is associated with an increase of 0.960 in the speed measure unconditionally, this effect is offset by 32% ($= -0.311/0.960$) when the New York City area experiences a flu peak epsiode. 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 Column (2) of Panel A, 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 Column (1). Further, 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.[18] Together, these findings document a causal effect of analyst inattention on the efficiency of information diffusion along economically linked firms, i.e. customers and suppliers.

In Column (3), we examine the interaction effect between institutional cross-holding and flu activity in the NYC area. Since most institutional investors are not located in the New York City area, we expect the coefficient of $Inst\ Cross\ Hold \times\ Peak\ Flu\ NY_t$ to be economically and statistically weaker than those for $Analyst\ Dual\ Cov \times\ Peak\ Flu\ NY_t$. Indeed, the results in Column (3) are consistent with our expectation. One can interpret the results in Column (3) as a placebo test for NYC peak flu episodes, i.e., the NYC peak flu episodes generate an interaction effect with information intermediaries if and only if these information intermediaries are located in the New York Area.

4.2.3 Robustness

We conduct several robustness tests. In Panel B of Table 4, X_{ijt} are replaced with dummy variables indicating the existence of dual-covering analysts, dual-covering brokers, and cross-holding institutional investors. Our results are very similar to those reported in Panel A. In Appendix Table A.4, we replace the dummy variable indicating peak flu incidence with the continuous measure of "percentage of flu tests with positive result". The results closely mirror our main findings reported in Table 4, indicating that our results are not sensitive to a particular cut-off level in defining 'peak flu'. Further, in another robustness check reported

[18] The coefficient estimate in Column (2) indicates a 23% decrease in the effect of dual-broker coverage on information diffusion speed.

in Appendix Table A.5, we repeat the tests in Table 4 using the "percentage of patient visits to healthcare-provider for influenz-like illness symptoms" (ILI) as an alternative flu activity measure. While this alternative flu measure is less informative about the prevalence of flu activity than our main measure, we find similar but slightly weaker results relative to those in Table 4.

We conduct a large number of additional robustness tests summarized in the specification chart in Figure 4. The chart displays the coefficient estimate and confidence intervals for our main variable of interest, $Analyst\ Dual\ Cov \times\ Peak\ Flu\ NY_t$, across a number of specifications, including additional control variables (i.e. the percentage of sales and cost of goods sold), alternative combinations of covariates, additional fixed effects specifications (e.g. including industry-by-year-by-quarter and supplier-customer pair fixed effects), and alternative levels of clustering standard errors. Further, in a few robustness checks, we exclude observations where the earnings announcements of both customers and suppliers are held within our estimation windows for the speed measure or where the earnings announcement dates in I/B/E/S and Compustata for the same earnings announcement event are different. Finally, we also carry out subsample analysis by splitting the full sample into two periods: 1996-2005 and 2006-2014. While the reported specification shown in Table 4 is highlighted in blue, none of these modifications mentioned above materially alters our main result.

4.2.4 Local Flu Incidence, Dual-Coverage and Cross-Holding, and Speed

Our previous tests reported in Table 4 mainly focus on flu incidence in the New York City area since it is where most sell-side analysts reside and work. This approach allows us to examine the full sample of I/B/E/S analysts. As noted earlier, to the extent that analysts located outside the NYC area are not affected by the flu, these tests would underestimate the effect of reduced attention on the speed of information diffusion. In addition, these tests are less powerful as they do not exploit geographic variation in flu incidence across regions.

In this subsection, we study flu peak activity at the geographic locations of dual-covering analysts and cross-holding institutional investors on the speed of supply-chain information diffusion. For these tests, the information about the work location of financial analysts is retrieved from FINRA BrokerCheck and location information of institutional investors is obtained from FactSet LionShares Ownership file.[19] Figures 2 and 3 provide an overview of the geographical distribution of financial analyst and institutional investor locations across all ten CDC regions. While more than half of financial analysts are located in the New York City area, institutional investors are located in several major financial centers dispersed in different CDC regions, such as New York City (Region 2), Boston (Region 1), Chicago (Region 5), San Francisco and Los Angeles (Region 9).

To test the effect of flu peak activity at the locations of dual-covering analysts on the speed of supply-chain information diffusion, we focus on the subsample of relationships where 1) there exists at least one dual-covering analyst, and 2) the location information of dual-covering analysts is available from FINRA BrokerCheck. We estimate the following regression in this subsample:

$$\begin{aligned} Speed_{i,j,t} = \alpha + \beta(Dual\ Analyst\ (Cross\ Owner)\ Local\ Flu_{i,j,t}) \\ + \delta_1 Z_{i,t} + \delta_2 Z_{j,t} + \delta_3 R_{i,j,t} + \delta_4 E_{i,t} + \gamma_i + \mu_j + \theta_t + \epsilon_{i,j,t} \end{aligned} \tag{5}$$

where control variables $Z_{j,t}$, $R_{i,j,t}$, and $E_{i,t}$ are defined as in Equations (3) and (4). We use two measures for Dual Analyst Local Peak Flu: *Dual Analyst, Local Peak Flu* (0/1) is a dummy variable that equals one if the location of at least one dual-covering analyst experiences local peak flu activities; *Dual Analyst, Local % Positive* is the average percentage of positive flu tests in the locations of the dual-covering analysts. The dummy variable aims to account for the possibility that the impact of flu is nonlinear to "the percentage of positive results in flu tests". The continuous variable addresses concerns about arbitrary cut-off levels in defining

[19]Information about analysts' work location, employment history, certifications etc. are obtained by scraping the FINRA BrokerCheck website. We match I/B/E/S and FINRA data based on an analyst's first and last name, employment history and current brokerage firm, and passage of the Series 86 and 86 exams since research analyst must hold these certifications to perform their job, according to FINRA Rule 1210 and FINRA Rule 1220(b)(6).

"flu peak activity". Since we control for relationship fixed effects in this test specification, β in Equation (5) captures the effect of local flu activities on the speed of information diffusion for the same customer-supplier relationship at different points in time.

[Insert Table 5 here.]

Columns (1) and (2) of Table 5 report our estimates of Equation (5). We find that the speed of information diffusion along supply chains is significantly reduced when dual-covering analysts are located in regions experiencing flu peak activities. For example, the coefficient estimate of *Dual Analyst – Local Peak Flu (0/1)* in Column (2) is -2.585, which is statistically significant at the 1% level. This estimate suggests that, when the locations of dual-covering analysts are affected by flu peak activities, the speed of supply-chain information diffusion is reduced by 11.08% relative to the unconditional mean of the speed measure. When we use the continuous measure, *Dual Analyst – Local % Positive*, to measure local flu activities in Column (1), the coefficient remains statistically significant at the 1% level. This result suggests that the pattern shown in Column (1) is not specific to a cut-off level that we use to define a local flu peak.

In Columns (3) and (4), we carry out a similar test based on flu peak activities at the locations of cross-holding institutional investors. Again, this test has to be carried out in a subsample of relationships where 1) there exists at least one cross-holding institutional investor, and 2) the location information of cross-holding institutional investors is available from FactSet LionShares Ownership file. Results in Columns (3) and (4) deliver a similar message: when the locations of cross-holding institutional investors are affected by flu activities, the speed of supply-chain information diffusion is significantly reduced. This result is especially noteworthy since we did not find a similarly significant effect for cross-holding investors when focusing on flu incidence in New York in Column (3) of Table 4.

5 Does Speed Matter for Investors and Firms?

5.1 Investors: Speed and the Customer Momentum 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. In contrast, our speed measure is a parsimonious way of capturing the many frictions that contribute to slow information diffusion. 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 suggested 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.

[Insert Table 6 here.]

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 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 $t-1$. 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.

Consistent with our expectation, the results in the Columns (1)-(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)-(6) of Panel A report results of customer momentum strategies when grouped by our 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 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 more profitable customer momentum strategy.

We repeat the above tests based on alphas after adjusting for the market factor, the Fama and French (1993) size and value factors, the Carhart (1997) momentum factor, and the Pástor 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. Taken collectively, the results in this section demonstrate that our speed measure captures important aspects of diffusion speed as suggested by earlier studies in the supply-chain literature.

5.2 Firms: Speed and Price Feedback Effects

A growing literature, starting with Luo (2005) and Chen et al. (2007), has documented that managers can glean signals from their firms' stock prices to inform corporate investment decisions, as market prices aggregate diverse information sets from thousands of market participants. Recent studies have presented further evidence for this price feedback effect, showing that managers also learn from information in the stock prices of economically linked firms, including industry peers (Foucault and Fresard, 2014) and supply chain partners (Liang et al., 2020). In this section we test whether the sensitivity of supplier investment to its own and to its customer's stock prices depends on the speed of supply-chain information diffusion.

5.2.1 Speed and Investment-to-Q sensitivity

The intuition for our tests is simple. Consider a customer information event where some of the revealed information is relevant to the investment decisions of their dependent suppliers. If customer-related information is rapidly reflected in supplier stock prices, supplier managers who look to stock prices for investment signals can rely more heavily on their own stock price for relevant customer information than when customer information diffuses more slowly. On the other hand, when supplier-relevant information in customer stock prices diffuses slowly, supplier stock prices are less informative about customers and supplier managers will rely less on their own stock price and more on their customer's stock price for guidance.

To test these predictions, we estimate supplier-investment-Q sensitivity regressions at the quarterly frequency as follows:

$$\begin{aligned} INV_{i,t}^{sup} = \alpha &+ \beta_1 Speed_{i,j,t-1} + \beta_2 Q_{i,t-1}^{sup} + \beta_3 Q_{j,t-1}^{cus} \\ &+ \beta_4 (Q_{i,t-1}^{sup} \times \ Speed_{i,j,t-1}) + \beta_5 (Q_{j,t-1}^{cus} \times \ Speed_{i,j,t-1}) \\ &+ controls + interaction\ terms + FEs + \epsilon_{i,j,t}. \end{aligned} \tag{6}$$

$INV_{i,t}^{sup}$ is one of two investment proxies: the change of property, plant, and equipment (PPE) and capital investment (CAPX), both scaled by PPE of supplier i in quarter t. $Q_{i,t-1}^{sup}$ and $Q_{j,t-1}^{cus}$ are the one-quarter lagged Tobin's Q of supplier i and customer j, respectively, and $Speed_{i,j,t-1}$ is the speed of supply chain information diffusion. We include lagged market leverage ($Leverage_{i,t-1}^{sup}$), operating cash flows ($CF_{i,t-1}^{sup}$), return on assets ($ROA_{i,t-1}^{sup}$), inventory turnover ($Inventory_{i,t-1}^{sup}$), and the inverse of total assets ($1/AT_{i,t-1}^{sup}$) of suppliers as additional control variables. Since we are investigating supplier-investment-Q sensitivities in this test, we also include interaction terms between these control variables and lagged supplier

Q as independent variables, following Edmans, Jayaraman, and Schneemeier (2017). In addition, we incorporate relationship and quarterly time fixed effects in our test specifications. Definitions of all variables are provided in Appendix A.1.

[Insert Table 7 here.]

Table 7 presents the results of estimating Equation (6). Panel A uses change in PPE as the dependent variable and Panel B focuses on capital expenditure. First, Column (1) of Panel A shows that the quarterly change in supplier assets is positively correlated with both $Q^{sup}_{i,t-1}$ and $Q^{cus}_{j,t-1}$ with coefficients equal to 0.058 and 0.010, respectively. Both coefficients are statistically significant at the 1% level. These findings are consistent with results in Chen et al. (2007) and Liang et al. (2020).

Our main result in Columns (2) shows that the speed of supply-chain information diffusion affects the sensitivity of supplier investment to both its own and to its customer's Q. The coefficient for $Q^{sup}_{i,t-1} \times \ Speed_{i,j,t-1}$ (Column 2) is positive (0.014) and statistically significant at the 1% level, indicating that the sensitivity of supplier investment to its own price increases with the speed of supply-chain information diffusion. For a one standard deviation increase in *Speed*, the sensitivity of supplier investment-to-Q increases by approximately 6% (= 0.2480 × 0.014/0.058).[20] In contrast, the coefficient on $Q^{cus}_{j,t-1} \times \ Speed_{i,j,t-1}$ is negative (-0.007) and statistically significant at the 5% level, suggesting that when customer information is more rapidly reflected in supplier stock price, supplier investment is less sensitive to customer stock price. In Columns (3) and (4), we replace year-quarter fixed effects with suppliers-industry-year-quarter and customers-industry-year-quarter fixed effects. This allows us to account for any industry trends in investment opportunities in both supplier and customer industries. Results reported in Columns (3) and (4) are qualitatively and quantitatively similar to those in Columns (1) and (2).

Considering the scaled capital expenditure as an alternative proxy for investment in Panel B of Table 7, we find similar results. For example, in Column (2) of Panel B, the

[20] In the interest of ease of legibility, we scale *Speed* by dividing by 100 in this table.

coefficient of $Q^{sup}_{i,t-1} \times$ $Speed_{i,j,t-1}$ is positive (0.009) 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 supplier-investment-Q sensitivity of 3% ($= 0.2480 \times 0.009/0.079$), consistent with our findings in Panel A. We note the coefficient of $Q^{cus}_{j,t-1} \times$ $Speed_{i,j,t-1}$, although still negative, becomes statistically insignificant.

Overall, these results are consistent with the hypothesis that customer-related information contained in supplier prices, as captured by the speed of supply-chain information diffusion, affects supplier manager investment decisions. Our findings suggest that as the speed of supply-chain information diffusion decreases, supplier stock prices reflect less customer-related private information (or, more broadly, reflect less of the market's assessment of that information), and supplier managers increasingly rely on the information contained in customer stock prices; on the other hand, when information diffusion speed is more rapid, more customer-related information is contained in supplier stock prices, and supplier managers rely more on their own stock prices for investment signals and less on customer stock prices. These findings suggest that understanding the extent to which customer information has already been reflected in their own stock prices can be of value to supplier managers.

5.2.2 Robustness

One potential concern for our findings in Table 7 is that firms often have longer horizons when making investment decisions. This would raise the question how our measure of information diffusion speed, estimated at the quarterly frequency, can possibly affect corporate investment decisions. As documented in Section 3, the lag-one autocorrelation of *Speed* is 0.685, indicating that our speed measure is a persistent characteristic of supply-chain relationships. To provide further evidence for this idea, we take the average *Speed* over the past year for each supplier-customer pair and implement tests similar to Equation (6) at the annual frequency. The results, summarized in Appendix Table A.6, are consistent with our main results and show a positive effect of *Speed* on investment-to-supplier-Q and a negative effect on investment-to-customer-Q sensitivity for three different investment proxies.

We conduct additional robustness tests controlling for dual broker and analyst coverage, stock price informativeness, and their interactions with supplier and customer Q in Appendix Table A.7. In Section 5.1 we argue that our speed measure is a parsimonious way of capturing the many frictions that contribute to slow information diffusion. Consistent with this idea, Panel A of Appendix Table A.7 documents that the inclusion of dual-analyst and dual-broker coverage interacted with Q does not alter the main effect of *Speed* on investment-to-Q sensitivities shown in Table 7. We also find that dual-coverage has a similar effect on investment-to-Q sensitivities as *Speed*, in line with the notion that dual-covering analysts contribute to information efficiency.

Next, we include measures of general price informativeness widely used in the literature, i.e. PIN (Easley, Kiefer, O'Hara, and Paperman, 1996; Easley, Kiefer, and O'Hara, 1997) and $1 - R2$ (Roll, 1988; Morck, Yeung, and Yu, 2000; Durnev, Morck, and Yeung, 2004), and their interactions with Q in Panel B. This helps us address the question if our speed measure captures aspects of information efficiency specific to the supply-chain setting. Consistent with Chen et al. (2007), the interaction effects of supplier-Q with the $1 - R2$ and PIN measures are positive and weakly significant. Importantly, our main findings for the effect of speed on supplier investment feedback are unchanged, suggesting that supply-chain information diffusion speed is not subsumed by traditional measures of price informativeness.

6 Information Diffusion and Investment Coordination

6.1 Coordination of Investment between Customers and Suppliers

Customer-supplier relationships often require a significant amount of relationship-specific investment (e.g., Williamson, 1975; Titman, 1984; Maksimovic and Titman, 1991; Raman and Shahrur, 2008). Previous studies, such as Cen, Dasgupta, and Sen (2016), suggest that more efficient coordination within customer-supplier relationships is often exhibited by higher correlation of customer and supplier investment.[21] The literature suggests that a more efficient information channel between customers and suppliers facilitates the coordination of investment by supply-chain partners. For example, previous studies have shown how private information sharing and public disclosure strategies facilitate investment coordination (e.g., Raman and Shahrur, 2008; Hui, Klasa, and Yeung, 2012). Our study suggests that information diffusion from customer to supplier *stock prices*, a public information channel that everyone can observe, may also facilitate the coordination of supplier and customer investments.

Following the literature on information sharing and the coordination of supply-chain investment, we predict that the coordination of supplier with customer investment, as proxied by the sensitivity of supplier investment to customer investment, will be positively correlated with the speed of supply-chain information diffusion. We test this prediction using the following specification:

$$\begin{aligned} INV_{i,t}^{sup} = \alpha + \beta_1 Speed_{i,j,t} + \beta_2 INV_{j,t}^{cus} + \beta_3 (INV_{j,t}^{cus} \times \ Speed_{i,j,t}) \\ + INV_{i,t-1}^{sup} + controls + FEs + \epsilon_{i,j,t}. \end{aligned} \tag{7}$$

$INV_{i,t}^{sup}$ ($INV_{j,t}^{cus}$) represents investment of the supplier i (customer j) in quarter t. We use the same investment measures as in Table 7, i.e. the change in property, plant, and equipment (ΔPPE) and capital investment (CAPX/PPE), both scaled by PPE. The results are reported in Table 8.

[Insert Table 8 here.]

Consistent with Cen et al. (2016), we find that the correlations between customer and supplier investments are positive and statistically significant. For example, when using ΔPPE of the supplier as the dependent variable in Column (1), the coefficients of ΔPPE

[21] Cen et al. (2016) show that the sensitivity of capital investments between customers and suppliers is significantly reduced after the supplier faces a higher likelihood of hostile takeovers, i.e., when the relationship is likely to be disrupted.

on the contemporaneous customer $\Delta PPE_{j,t}^{cus}$ is 0.028, which is statistically significant at the 1% level.

The most striking result in Table 8 is that the speed of supply-chain information diffusion affects the correlation between customer and supplier investments. In Column (1), the coefficient of $\Delta PPE_{j,t}^{cus} \times \ Speed_{i,j,t}$ is 0.063 (statistically significant at the 1% level). This translates to a 62.5% (= 0.24799 × 0.063/0.025) increase in the correlation between the change in PPE of customers and suppliers, based on the coefficient of $\Delta PPE_{j,t}^{cus}$ (0.025).

One major endogeneity concern under this specification is that both the speed of information diffusion and the investment coordination along the supply chain are determined by the strength of supply-chain relationships. Therefore, a positive and significant coefficient of $\Delta PPE_{j,t}^{cus} \times \ Speed_{i,j,t}$ in Column (1) does not necessarily mean that fast speed of information diffusion facilitates investment coordination along the supply chain. To address this concern, we include two explicit measures for supply-chain relationship strength, the percentage of sales to customer in the supplier's total sales (*Pct of Sales Sup*) and the percentage of sales to customer in the customer's cost of goods sold (*Pct of COGS Cus*), and their interaction terms with our speed measure in the test specification reported in Column (2). The coefficient of the interaction term $\Delta PPE_{j,t}^{cus} \times \ Pct of COGS Cus$ is indeed positive and statistically significant, which confirms our conjecture that the degree of supply-chain investment coordination is positively correlated with the strength of supply-chain relationships. However, even after we control for the interaction terms between relationship strength measures and $\Delta PPE_{j,t}^{cus}$, the coefficient of $\Delta PPE_{j,t}^{cus} \times \ Speed_{i,j,t}$ remains positive and statistically significant. While the test reported in Column (2) cannot rule out all endogeneity concerns driven by unknown economic mechanisms that simultaneously affect both the speed of information diffusion and the investment coordination along the supply chain, it does address the major concern that our results are driven by the strength of supply-chain relationships. Our results are similar when using scaled capital expenditure as our investment proxy in Columns (3) and (4). Overall, our results are consistent with the notion that fast speed of supply-chain information diffusion in stock prices facilitates coordination in real investments between customers and suppliers.

As a robustness test, we further augment the specification in Equation (7) by including additional interaction terms, $INV_{j,t}^{cus} \times PI_{i,t}^{sup}$ and $INV_{j,t}^{cus} \times PI_{j,t}^{cus}$, where $PI_{i,t}^{sup}$ ($PI_{j,t}^{cus}$) is one of the traditional price informativeness measures (PIN and 1-R2) for both the customer and the supplier firm. We add one additional interaction term each time and all other variables, controls, and fixed effects are similar to Equation (7). The results reported in Appendix Table A.8 show no discernible pattern with respect to the additional interaction terms. This finding is consistent with our expectation that, relative to supply-chain information, unspecified information captured by the 1-R2 and PIN measures is less likely to enhance the coordination of investment along the supply chain. Further, including these additional interaction terms does not affect the empirical patterns reported in Table 8.

6.2 Substitutes or Complements: Public vs. Private Information Sharing Channels between Customers and Suppliers

Previous studies have shown how private information sharing (e.g., daily interactions between customers and suppliers on inventory management and quality monitoring) also facilitates investment coordination between customers and suppliers (e.g., Raman and Shahrur, 2008). In this subsection, we address the following two related questions. First, are these private information sharing channels always reflected in the speed of information diffusion in stock prices? If not, are private information sharing channels and the information diffusion in stock prices substitutes or complements with respect to investment coordination between customers and suppliers.

We use the geographical distance between the headquarters of customers and suppliers to proxy for private information sharing between customers and suppliers. The underlying assumption is that geographical proximity enables more frequent face-to-face interactions and provides more opportunities of information sharing (e.g., Coval and Moskowitz, 2001;

Malloy, 2005).[22] The geographical distance is measured by the driving time (hours) between the headquarters of customers and suppliers, according to the Google Maps API.

We first include the measure of private information sharing channels as an additional independent variable in Equation (3), to examine whether they are correlated with our speed measure. The results, reported in Appendix Table A.9, show that the geographical distance between the headquarters of customers and suppliers are not correlated with our speed measure, indicating that at least some private information sharing channels between customers and suppliers are orthogonal to the information diffusion through stock prices.

Next we examine whether private information sharing channels, proxied by the geographical distance measure, are substitutes or complements for the information diffusion channel via stock prices with respect to facilitating investment coordination between customers and suppliers. We partition the observations used in Table 8 into two subsamples based on our private information sharing measure and repeat the estimation of Equation (7) in these two subsamples. This test allows us to examine whether the speed of information diffusion via stock prices generates significantly different impacts on the investment coordination conditional on the strength of private information sharing between customers and suppliers. Results are reported in Table 9.

[Insert Table 9 here.]

In the left panel of Table 9, investment is measured as the change of property, plant, and equipment (ΔPPE). We first partition all observations based on the driving distance: results for relationships with high and low driving distances are reported in Columns (1) and (2), respectively. We find that the coefficient of the interaction term, $\Delta PPE^{cus}_{j,t} \times \ Speed_{i,j,t}$, is much larger for the high driving distance subsample (0.106 vs. 0.004). The difference is statistically significant at the 1% level. This pattern is robust when investment is proxied by

[22] Coval and Moskowitz (2001) point out that, between investors and firms that they invest, "investors located near a firm can visit the firm's operations, talk to suppliers and employees, as well as assess the local market conditions in which the firm operates". A similar argument also applies between customers and suppliers.

CAPX/PPE in the right panel of Table 9. Our results in Table 9 suggest that the speed of information diffusion via stock prices are more important for investment coordination between customers and suppliers when other private information sharing channels are weaker. Put differently, the information diffusion via stock prices and some private information sharing mechanisms are substitutes while facilitating investment coordination along the supply chain.

7 Conclusion

Based on the methodology of Mech (1993) and Hou and Moskowitz (2005), we develop a measure of the speed of information diffusion along supply chains. Our measure is computed using daily stock return residuals of customers and suppliers around the earnings announcement dates of customer firms. We find that the attention of key market participants, such as financial analysts and 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.

To address concerns related to endogenous analyst dual-coverage and institutional cross-holding, we exploit regional flu epidemics as exogenous shocks to the attention of dual-covering analysts and cross-holding institutional investors. In particular, we compare the same analyst dual-covering the same customer-supplier firm pair at different points in time, exploiting geographic and time-series variations of flu exposure in the location of the analyst. We find that inattention of analysts due to local flu peak activities has a negative causal effect on both the likelihood of an analyst participating and actively asking question in conference calls and the speed of information diffusion from customer to supplier.

We further demonstrate that our measure of supply-chain information diffusion speed can be useful to both investors and corporate managers. We show that *Speed* helps investors enhance the customer momentum strategies by accurately identifying relationship-pairs with slow information diffusion. We also document that information efficiency of prices as measured by *Speed* increases investment-to-Q sensitivity of supplier firms with supplier stock prices and decreases investment-to-Q sensitivity with customer stock prices. This finding indicates that for supplier managers relying on stock prices for investment feedback, understanding the extent to which customer-related information is already reflected in their stock prices can be of value. In the same vein, we show that investment coordination between suppliers and customers is strengthened with high speed of information diffusion, and that coordination via public information sharing channels (e.g., stock prices) can act as a substitute for private information sharing channels (e.g., private communications).

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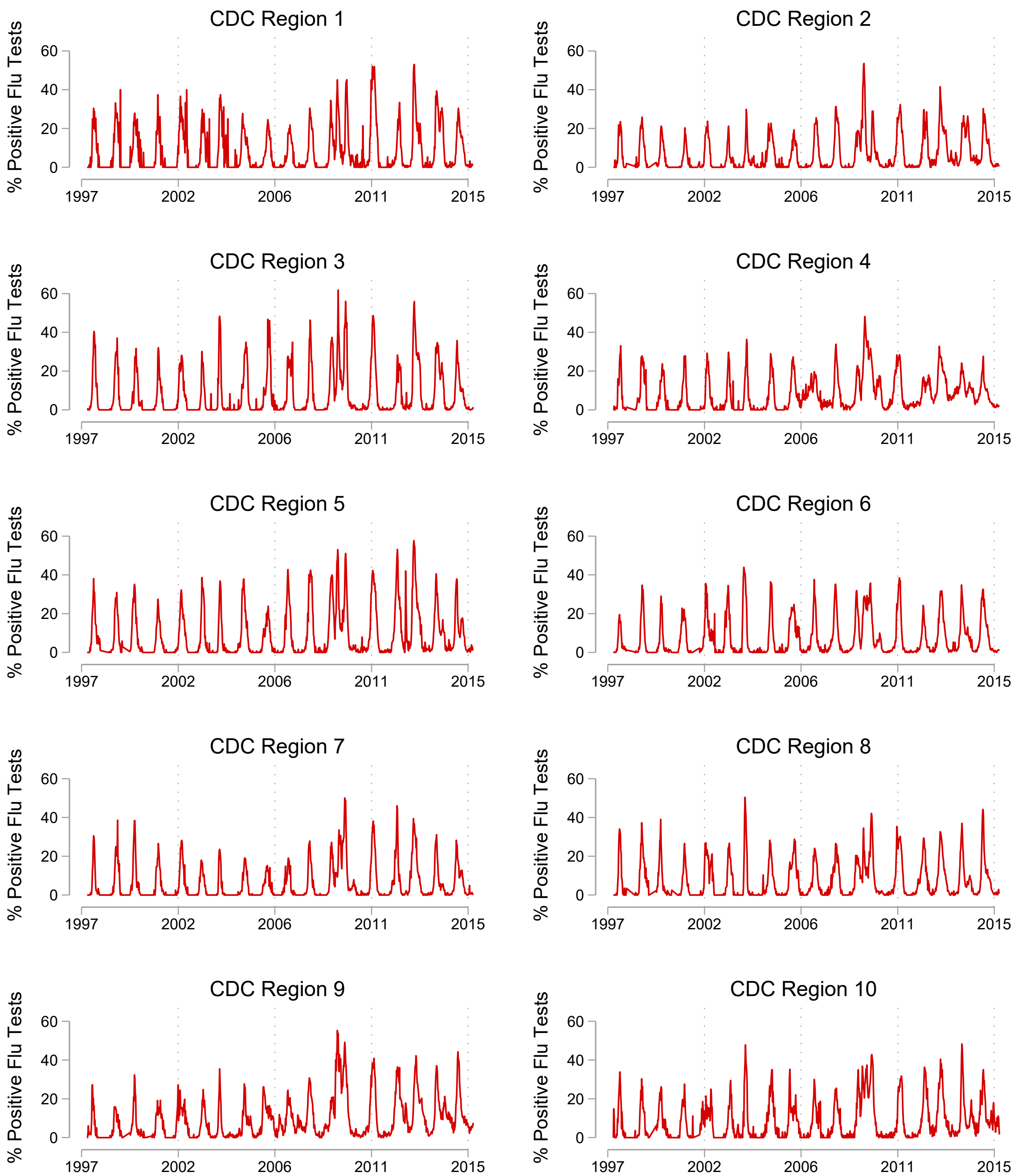
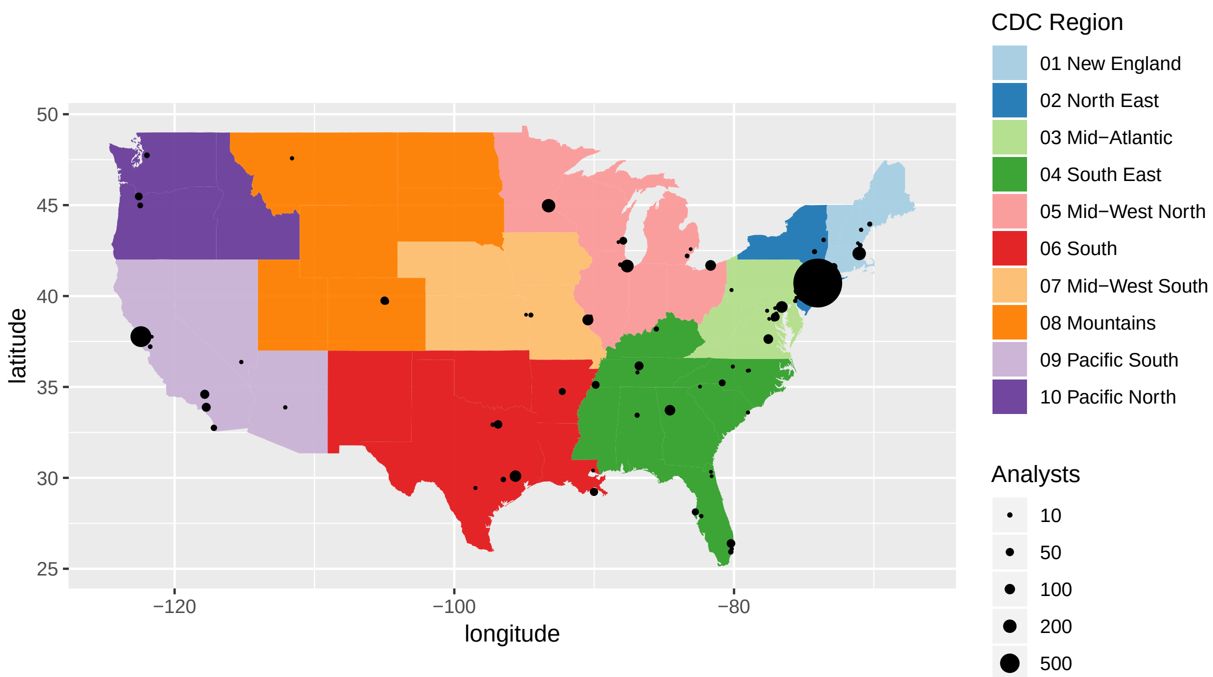
Figure 1: Time Series of Flu Measure by CDC Region



Data collected by WHO/NREVSS Collaborating Laboratories.
Obtained from Center for Disease Control (CDC) website.

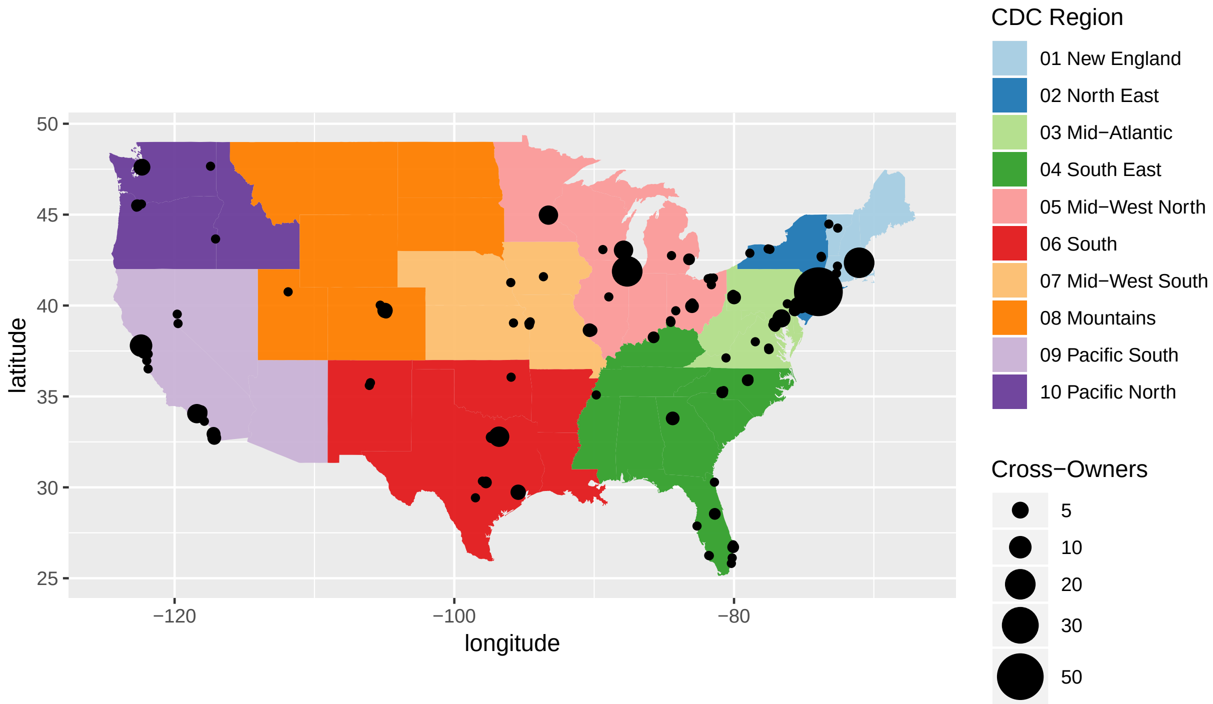
Notes: These figures plot the weekly "percentage of flu tests with a positive result" (PP) obtained from WHO/NREVSS Laboratories by CDC Region.

Figure 2: Locations of Analysts across CDC Regions



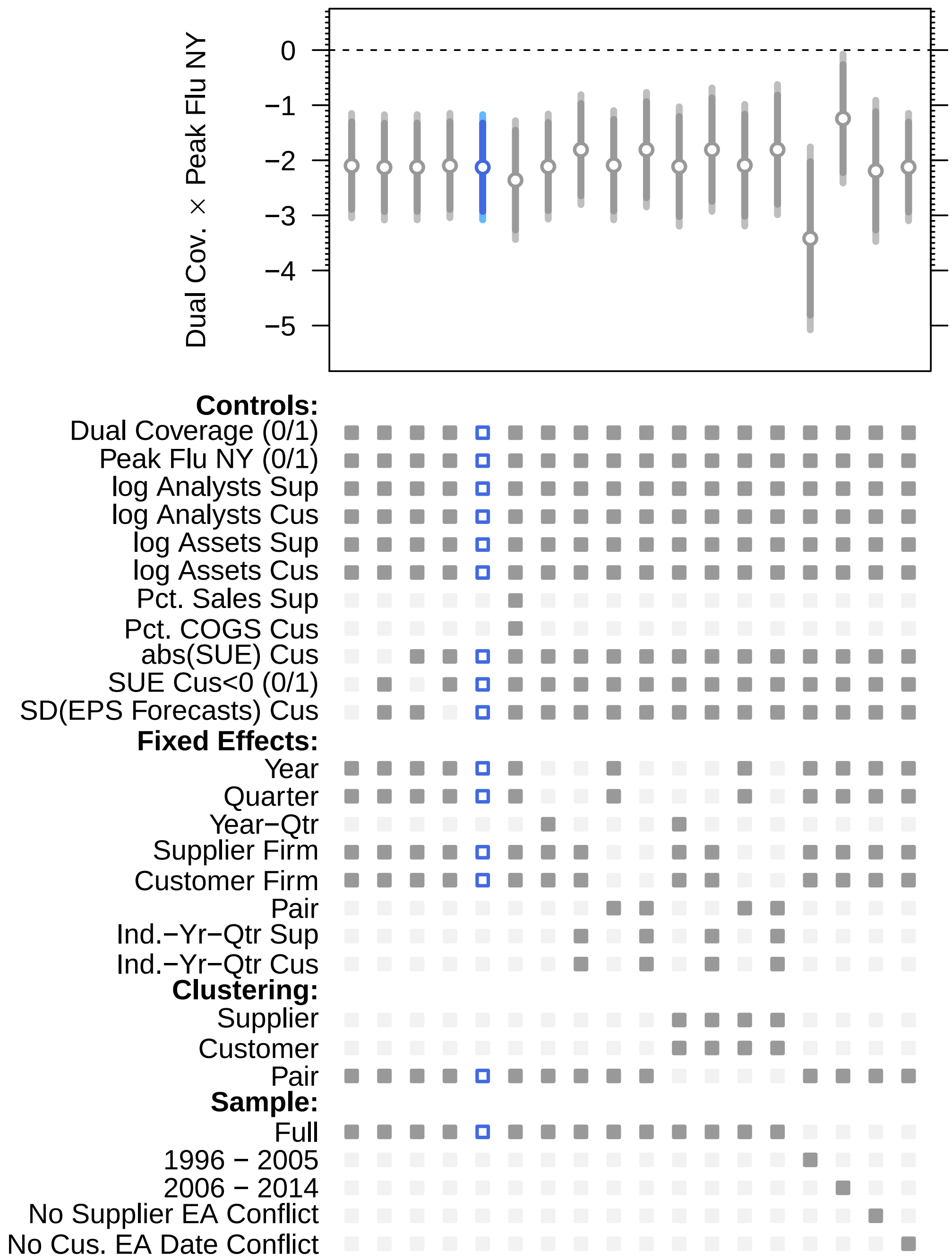
Notes: This figure shows the locations of the equity analysts in our sample across the ten CDC regions in the U.S. The sample is constructed by merging equity analysts from IBES with detailed location data from the FINRA BrokerCheck website.

Figure 3: Locations of Institutional Investors across CDC regions



Notes: This figure shows the locations of the institutional investors who cross-own both supplier and customer in our sample across the ten CDC regions in the U.S. The location data is obtained from the Factset LionShares database.

Figure 4: Specification Chart – Effect of NY Flu on Speed of Inf. Diffusion



Notes: This figure summarizes the coefficient estimate for our main coefficient of interest in Equation (4), *Dual Analyst Cov* × *Peak Flu NY* (0/1), for various specifications. The specification highlighted in blue is our preferred model as shown in Table column (1) of Table 4. The light (dark) grey bars indicate the 95% (90%) confidence interval. *No Supplier EA Conflict* drops all observations where the supplier had an earnings announcement up to 10 days before or after the customer's EA. *No Cus. EA Date Conflict* drops observations where the customer earnings announcement date in Compustat and I/B/E/S differs.

Table 1: Summary Statistics

Notes: This table provides summary statistics for our main dependent and independent variables. Panel A summarizes the main measure of the speed of information diffusion along the supply-chain, estimated around the customer firms' earnings announcements (EA). The dataset is organized at the supplier-customer pair-quarter level. Panel B provides summary statistics of supplier-customer relationship characteristics at the pair-quarter level. *Num Dual Analysts*, *Num Dual Brokers*, and *Num Cross Owners* are the number of dual-covering analysts and brokerage firms, and the number of cross-owning, active institutional investors in a given quarter. *Dual Analyst (0/1)*, *Dual Broker (0/1)*, and *Cross Owner (0/1)* are the corresponding indicator variables. Analyst and broker coverage data is from I/B/E/S, institutional ownership data is from FactSet Lionsshares. *HQ Driving Distance (h)* is the estimated driving time from the supplier to the customer headquarter according to the Google Maps API, *Relationship Length* is the number of years since the inception of the customer-supplier relationship. *Pct of Sales Sup* and *Pct of COGS Cus* capture the proportion of total sales (cost of goods sold) the customer (supplier) represents to the supplier (customer). Panels C and D present summary statistics of financial and accounting variables for suppliers (Panel C) and customers (Panel D) in our sample. The two panels show summary statistics for unique supplier firm-quarters and customer firm-quarters, respectively. All financial data are obtained from Compustat, and winsorized at the 5% level within the full Compustat universe. PIN measures are computed following Brown and Hillegeist (2007) and obtained from Stephen Brown's website. Detailed variable definitions and data sources are provided in Appendix Table A.1.

Panel A: Quarterly Speed Measures

	N	Mean	StDev	p25	Median	p75
Speed	107156	23.332	24.799	3.312	14.160	36.505
Speed Raw	107156	40.792	31.847	10.246	36.561	68.537
Speed FF3	107156	23.023	24.525	3.296	13.928	35.837

Panel B: Unique Supplier-Customer Relationship-Quarters

	N	Mean	StDev	p25	Median	p75
Num Dual Analysts	107156	0.815	2.406	0.000	0.000	0.000
Dual Analyst (0/1)	107156	0.232	0.422	0.000	0.000	0.000
Num Dual Brokers	107156	3.310	4.804	0.000	1.000	5.000
Dual Broker (0/1)	107156	0.603	0.489	0.000	1.000	1.000
Num Cross Owners	107156	0.882	1.523	0.000	0.000	1.000
Cross Owner (0/1)	107156	0.402	0.490	0.000	0.000	1.000
HQ Driving Distance (h)	90923	16.475	13.239	5.547	13.284	25.219
Relationship Length	107156	4.348	4.056	2.000	3.000	6.000
Pct of Sales Sup	86661	0.176	0.186	0.090	0.135	0.210
Pct of COGS Cus	85913	0.017	0.057	0.000	0.002	0.009

Panel C: Unique Supplier Firm-Quarters

	N	Mean	StDev	p25	Median	p75
Total Assets (AT)	100995	1057.687	2630.955	33.500	123.489	625.080
ln(1+AT)	100995	5.028	2.017	3.541	4.824	6.439
Market Capitalization	100553	957.980	2080.777	32.285	137.994	663.627
ln(1+MCap)	100553	5.039	2.036	3.505	4.934	6.499
Num Analysts	101765	4.539	5.772	0.000	2.000	7.000
ln(1+Analysts)	101765	1.174	1.054	0.000	1.099	2.079
ΔPPE	83397	0.027	0.097	-0.024	0.006	0.053
ln(1+ΔPPE)	83397	0.022	0.090	-0.024	0.006	0.052
Capx/PPE	98622	0.295	0.206	0.138	0.240	0.411
ln(1+Capx/PPE)	98622	0.247	0.151	0.129	0.215	0.344
Tobin's Q	84072	2.042	1.536	1.118	1.493	2.309
ln(1+Q)	84072	1.026	0.383	0.750	0.914	1.197
1/AT	85154	0.025	0.056	0.001	0.007	0.024
ROA	85046	-0.007	0.058	-0.011	0.009	0.022
Inv. Turnover	82999	0.855	0.807	0.211	0.686	1.236
CF/AT	75842	0.010	0.067	0.002	0.019	0.034
Mkt. Leverage	80408	0.199	0.216	0.009	0.124	0.324
PIN	62388	0.219	0.135	0.125	0.189	0.281
$1-R^2$	96744	0.818	0.171	0.748	0.880	0.941

Panel D: Unique Customer Firm-Quarters

	N	Mean	StDev	p25	Median	p75
Total Assets (AT)	41910	5850.789	5475.977	1009.704	3512.000	11928.578
ln(1+AT)	41910	7.910	1.520	6.918	8.164	9.387
Market Capitalization	41866	4511.191	3700.009	913.593	3390.914	9280.480
ln(1+MCap)	41866	7.745	1.469	6.818	8.129	9.136
Num Analysts	42541	15.454	10.506	7.000	15.000	23.000
ln(1+Analysts)	42541	2.461	1.000	2.079	2.773	3.178
ΔPPE	40894	0.027	0.075	-0.008	0.013	0.044
ln(1+ΔPPE)	40894	0.024	0.069	-0.008	0.013	0.043
Capx/PPE	41341	0.250	0.148	0.149	0.215	0.313
ln(1+Capx/PPE)	41341	0.217	0.111	0.139	0.195	0.272
Tobin's Q	40578	2.000	1.292	1.213	1.569	2.287
ln(1+Q)	40578	1.034	0.332	0.794	0.943	1.190
Abs(SUE)	42541	0.003	0.005	0.000	0.001	0.003
SUE Negative (0/1)	42541	0.350	0.477	0.000	0.000	1.000
StDev(EPS Forecasts)	40287	0.040	0.050	0.010	0.020	0.050
PIN	27637	0.127	0.074	0.079	0.113	0.161
$1-R^2$	42487	0.675	0.205	0.535	0.709	0.844

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

Notes: This table reports OLS regression estimates of the speed of supply-chain information diffusion (*Speed*) on analyst dual-coverage, broker dual-coverage, and institutional cross-holding. The dependent variable in all specifications is the speed of supply-chain information diffusion, measured around earnings announcements of the customer firms. In Panel A, *Num Dual Analysts* is the number of analysts who simultaneously cover both the customer and the supplier in the relationship-quarter. Similarly, *Num Dual Brokers* is the number of brokerage firms simultaneously covering the customer and supplier in the relationship-quarter. *Num Cross Owners* is the number of active institutional investors who own at least 5% of outstanding shares of both the customer and the supplier firms in the relationship-quarter. In Panel B, *Dual Analyst* (0/1), *Dual Broker* (0/1), and *Cross Owner* (0/1) are the corresponding dummy variables, each taking the value of 1 if the supplier-customer pair has at least one dual-covering analyst, dual-covering broker, or cross-holding institutional investor, respectively. Detailed definitions of all independent variables are provided in Appendix A.1. Supplier, customer, and quarterly time-fixed effects are included 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: Continuous measures of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed				
	(1)	(2)	(3)	(4)	(5)
Num Dual Analysts	0.883***			0.875***	
	(9.99)			(9.98)	
Num Dual Brokers		0.374***			0.373***
		(7.32)			(7.30)
Num Cross Owners			0.307***	0.269***	0.301***
			(3.64)	(3.24)	(3.58)
ln(1+Analysts) Sup	0.849***	0.657***	1.031***	0.813***	0.616**
	(3.61)	(2.75)	(4.33)	(3.45)	(2.58)
ln(1+Analysts) Cus	0.111	0.162	0.193	0.061	0.105
	(0.54)	(0.78)	(0.93)	(0.29)	(0.50)
ln(Total Assets) Sup	0.789***	0.692***	1.048***	0.780***	0.681***
	(3.19)	(2.78)	(4.22)	(3.15)	(2.73)
ln(Total Assets) Cus	0.917*	0.878*	1.038**	0.915*	0.875*
	(1.85)	(1.76)	(2.08)	(1.85)	(1.75)
Abs(SUE) Cus	14.583	19.197	20.564	15.279	19.930
	(0.60)	(0.79)	(0.84)	(0.62)	(0.82)
SUE negative (0/1)	-0.253	-0.266	-0.245	-0.244	-0.256
	(-1.33)	(-1.39)	(-1.28)	(-1.28)	(-1.34)
SD(EPS Forecasts) Cus	11.848***	11.477***	11.842***	11.859***	11.490***
	(3.64)	(3.53)	(3.64)	(3.65)	(3.53)
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes
Observations	103949	103949	103949	103949	103949
R^2	0.131	0.130	0.129	0.131	0.130

Panel B: Dummy variables of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed				
	(1)	(2)	(3)	(4)	(5)
Dual Analyst (0/1)	2.190***			2.193***	
	(6.24)			(6.25)	
Dual Broker (0/1)		0.691**			0.692**
		(2.19)			(2.20)
Cross Owner (0/1)			0.129	0.149	0.132
			(0.50)	(0.58)	(0.52)
ln(1+Analysts) Sup	0.936***	0.970***	1.068***	0.928***	0.963***
	(3.94)	(3.99)	(4.48)	(3.91)	(3.95)
ln(1+Analysts) Cus	0.195	0.233	0.243	0.185	0.224
	(0.93)	(1.12)	(1.17)	(0.89)	(1.07)
ln(Total Assets) Sup	0.985***	0.999***	1.057***	0.979***	0.995***
	(3.96)	(3.98)	(4.25)	(3.94)	(3.96)
ln(Total Assets) Cus	0.928*	1.013**	1.037**	0.922*	1.007**
	(1.87)	(2.03)	(2.07)	(1.86)	(2.02)
Abs(SUE) Cus	18.061	19.754	19.917	18.171	19.854
	(0.74)	(0.81)	(0.81)	(0.74)	(0.81)
SUE negative (0/1)	-0.248	-0.257	-0.255	-0.247	-0.256
	(-1.30)	(-1.34)	(-1.33)	(-1.29)	(-1.34)
SD(EPS Forecasts) Cus	11.702***	11.801***	11.834***	11.707***	11.805***
	(3.60)	(3.63)	(3.64)	(3.60)	(3.63)
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes
Observations	103949	103949	103949	103949	103949
R^2	0.129	0.129	0.129	0.129	0.129

Table 3: Local Flu Incidence and Earnings Conference Call Participation

Notes: This table reports linear probability estimates of analyst conference call participation on local flu incidence. The dependent variable is a dummy variable indicating if an analyst who covers the firm (has made at least one earnings forecast in the current year) is present on the conference call. *Local % Positive* is the percentage of flu tests with positive results in the analyst's location in the current week and *Peak Local Flu* (*PP*) is a dummy that takes the value of one if there is a peak flu episode in the analyst's location, and zero otherwise. Each regression includes the following controls: *Analyst Coverage* is the number of analysts covering the firm, *Allstar Analyst* (0/1) indicates if an analyst has received an Allstar designation from Morningstar, *Analyst Tenure* is the number of years an analyst has been with a brokerage firm, and *Top* 10 *Brokerage* indicates the ten largest brokerages. *#Industries covered*, *#Forecasts per Firm*, and # *Stocks* covered are the number of industries covered, the number of forecasts per firm, and the number of different stocks covered by the analyst in the current year, respectively. Day-of-week, year-by-week, analyst-by-broker-by-firm, and conference call fixed effects are included as indicated. t-statistics in parentheses are computed based on standard errors clustered at the analyst-by-broker-by-firm level in all specifications. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Call Participation (0/1)			
	(1)	(2)	(3)	(4)
Local % Positive	-0.000382***		-0.000481***	
	(-3.02)		(-3.48)	
Peak Local Flu (PP)		-0.00575**		-0.00728**
		(-2.15)		(-2.46)
Analyst Coverage	-0.00146***	-0.00146***		
	(-4.58)	(-4.58)		
Allstar Analyst (0/1)	0.0268***	0.0268***	0.0310***	0.0310***
	(6.65)	(6.66)	(8.03)	(8.03)
Analysts Tenure	-0.00306	-0.00305	-0.00219	-0.00216
	(-1.64)	(-1.63)	(-1.13)	(-1.11)
Top 10 Brokerage	-0.00333	-0.00308	-0.00646	-0.00616
	(-0.74)	(-0.69)	(-1.45)	(-1.39)
# Industries covered	0.00309**	0.00310**	0.00236**	0.00237**
	(2.47)	(2.48)	(1.97)	(1.98)
# Forecasts per Firm	0.00142***	0.00142***	0.00143***	0.00143***
	(14.30)	(14.30)	(14.08)	(14.08)
# Stocks covered	0.000110	0.000110	0.000698**	0.000697**
	(0.37)	(0.37)	(2.40)	(2.40)
Day-of-Week FE	Yes	Yes	No	No
Year-by-Week FE	Yes	Yes	No	No
Analyst-by-Broker-by-Firm FE	Yes	Yes	Yes	Yes
Conference Call FE	No	No	Yes	Yes
Observations	487640	487640	482269	482269
R^2	0.464	0.464	0.616	0.616

Table 4: Flu in New York – Dual-Coverage, Cross-Holdings, and Speed

Notes: This table presents results of the interaction effect between peak flu incidence in the New York (NY) area and analyst/broker dual-coverage and institutional cross-holding on the speed of information diffusion. The dependent variable in all specifications is the speed of supply-chain information diffusion, measured around earnings announcements of the customer firms. In Panel A, *Num Dual Analysts* is the number of analysts who simultaneously cover both the customer and supplier in the current relationship-quarter. Similarly, *Num Dual Brokers* is the number of brokerage firms simultaneously covering both the customer and supplier in the relationship-quarter. *Num Cross Owners* is the number of active institutional investors who cross-own both the customer and supplier in the relationship-quarter. In Panel B, *Dual Analyst* (0/1), *Dual Broker* (0/1), and *Cross Owner* (0/1) are the corresponding dummy variables, each taking the value of 1 if the supplier-customer pair has at least one dual-covering analyst, dual-covering broker, or cross-holding institutional investor, respectively. *Peak Flu NY* is a dummy variable that equals one if there is a peak flu episode in the New York area based on the 'percentage of flu tests with positive results' from WHO/NREVSS laboratories. We include similar controls as in Table 2. Detailed definitions of dependent and independent variables are provided in Appendix A.1. We include supplier, customer, 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: Continuous measures of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed		
	(1)	(2)	(3)
Num Dual Analysts	0.959***		
	(10.67)		
Num Dual Brokers		0.392***	
		(7.53)	
Num Cross Owners			0.345***
			(3.85)
Peak Flu NY (0/1)	-0.376	-0.320	-0.672**
	(-1.43)	(-1.10)	(-2.37)
Num Dual Analysts × Peak Flu NY (0/1)	-0.311***		
	(-3.40)		
Num Dual Brokers × Peak Flu NY (0/1)		-0.092**	
		(-2.05)	
Num Cross Owners × Peak Flu NY (0/1)			0.025
			(0.20)
Sup./Cus./EA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	99868	99868	99868
R^2	0.131	0.130	0.129

Panel B: Dummy variables of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed		
	(1)	(2)	(3)
Dual Analyst (0/1)	2.621***		
	(7.06)		
Dual Broker (0/1)		1.019***	
		(3.05)	
Cross Owner (0/1)			0.198
			(0.71)
Peak Flu NY (0/1)	-0.142	0.291	-0.536*
	(-0.52)	(0.83)	(-1.74)
Dual Analyst × Peak Flu NY (0/1)	-2.126***		
	(-4.37)		
Dual Broker × Peak Flu NY (0/1)		-1.483***	
		(-3.74)	
Cross Owner × Peak Flu NY (0/1)			-0.247
			(-0.62)
Sup./Cus./EA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	99868	99868	99868
R^2	0.130	0.129	0.129

Table 5: Local Flu Incidence – Dual-Coverage, Cross-Holdings, and Speed

Notes: This table presents the effect of flu incidence at the locations of dual-covering analysts and cross-holding institutional investors on the speed of information diffusion along supply chains. Speed in this table is scaled to be between 0 and 100. The sample includes only supplier-customer relationship-quarter observations which have analyst dual-coverage (Columns 1 and 2) or institutional cross-holding (Columns 3 and 4), respectively. *Dual Analyst – Local Peak Flu* (0/1) is a dummy variable that equals to 1 if the location of at least one dual-covering analyst experiences a peak flu activity. *Dual Analyst – Local % Positive* indicates the average percentage of positive flu tests in the locations of the dual-covering analysts. *Cross Owner – Local Peak Flu* (0/1) and *Cross Owner – Local % Positive* are defined similarly for peak flu activities at the location of cross-holding institutional investors. Location information of dual-covering analysts is obtained from FINRA BrokerCheck. Location information of institutional investors is obtained from the FactSet LionShares Ownership database. Detailed definitions of dependent and independent variables are provided in Appendix A.1. 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: Speed			
	Has Dual Coverage		Has Cross-Owner	
	(1)	(2)	(3)	(4)
Dual Analyst - Local % Positive	-0.081***			
	(-2.59)			
Dual Analyst - Local Peak Flu		-2.556***		
		(-4.17)		
Cross Owner - Local % Positive			-0.041***	
			(-2.59)	
Cross Owner - Local Peak Flu				-0.732*
				(-1.91)
Supplier Controls	Yes	Yes	Yes	Yes
Customer Controls	Yes	Yes	Yes	Yes
EA Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	15041	15358	40354	40354
R^2	0.256	0.256	0.223	0.223

Table 6: Speed and Customer Momentum Strategies

Notes: 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 statistical significance at the 10%, 5% and 1% level, 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 and the Supplier Price-Investment Feedback

Notes: This table summarizes panel regressions of the quarterly investment of suppliers on the one-quarter lagged supplier Q ($Q^{sup}_{i,t-1}$), lagged customer Q ($Q^{cus}_{j,t-1}$), and the interaction terms between lagged supplier- and customer Q and the speed measure ($Q^{sup}_{i,t-1} \times Speed_{i,j,t-1}$ and $Q^{cus}_{j,t-1} \times Speed_{i,j,t-1}$). The measure of firm investment in Panel A is the change in supplier PPE, Panel B uses supplier capital expenditure (Capx), both scaled by lagged PPE. Investment and Q measures are log-transformed to account for outliers. The dataset is organized at relationship-quarter level. We also include the following lagged firm characteristics of suppliers as control variables: market leverage, cash flow scaled by assets (CF/AT), ROA, inventory turnover, the inverse of the total assets, and their interactions with supplier Q. We include relationship, year-by-quarter, and supplier- and customer-industry-by-quarter (2 digit SIC codes) fixed effects as indicated. 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: Supplier Growth in PPE (ΔPPE)

	Dependent Variable: ΔPPE Sup			
	(1)	(2)	(3)	(4)
Speed t-1	-0.008**	-0.002	-0.006*	0.002
	(-2.55)	(-0.59)	(-1.73)	(0.36)
Q Sup t-1	0.058***	0.058***	0.058***	0.057***
	(22.84)	(22.73)	(20.74)	(20.60)
Q Cus t-1	0.010***	0.012***	0.004	0.007
	(3.48)	(3.97)	(1.03)	(1.62)
(Q × Speed) Sup t-1	0.012***	0.014***	0.009***	0.011***
	(4.02)	(4.33)	(3.00)	(3.41)
(Q × Speed) Cus t-1		-0.007**		-0.009**
		(-1.99)		(-2.45)
1/Total Assets Sup t-1	-0.165***	-0.165***	-0.165***	-0.166***
	(-5.73)	(-5.75)	(-5.07)	(-5.09)
ROA Sup t-1	0.152***	0.152***	0.124***	0.124***
	(12.94)	(12.95)	(9.75)	(9.75)
Inventory TO Sup t-1	-0.004***	-0.004***	-0.004***	-0.004***
	(-4.04)	(-4.04)	(-3.57)	(-3.57)
Mkt. Leverage Sup t-1	-0.050***	-0.049***	-0.051***	-0.050***
	(-5.29)	(-5.28)	(-4.96)	(-4.96)
Q Sup t-1 × Mkt. Leverage Sup t-1	-0.042***	-0.042***	-0.037**	-0.037**
	(-3.16)	(-3.17)	(-2.56)	(-2.57)
CF/AT Sup t-1	-0.018	-0.018	0.005	0.005
	(-0.79)	(-0.79)	(0.20)	(0.20)
Q Sup t-1 × CF/AT Sup t-1	-0.003	-0.003	-0.015	-0.014
	(-0.21)	(-0.21)	(-0.86)	(-0.85)
Year-Qtr FE	Yes	Yes	No	No
Sup Ind-by-Year-Qtr FE	No	No	Yes	Yes
Cus Ind-by-Year-Qtr FE	No	No	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	95374	95374	93694	93694
R^2	0.356	0.356	0.468	0.468

Panel B: Supplier Capx/PPE

	Dependent Variable: Capx/PPE Sup			
	(1)	(2)	(3)	(4)
Speed t-1	-0.005	-0.008*	-0.004	-0.004
	(-1.24)	(-1.66)	(-1.00)	(-0.75)
Q Sup t-1	0.079***	0.079***	0.069***	0.069***
	(20.16)	(20.15)	(15.94)	(15.91)
Q Cus t-1	0.018***	0.017***	0.008	0.008
	(3.47)	(3.15)	(1.18)	(1.16)
(Q × Speed) Sup t-1	0.010***	0.009**	0.008**	0.008**
	(2.80)	(2.50)	(2.20)	(2.14)
(Q × Speed) Cus t-1		0.004		0.000
		(1.02)		(0.02)
1/Total Assets Sup t-1	-0.006	-0.006	-0.015	-0.015
	(-0.15)	(-0.14)	(-0.32)	(-0.32)
ROA Sup t-1	0.146***	0.146***	0.110***	0.110***
	(9.48)	(9.48)	(7.07)	(7.07)
Inventory TO Sup t-1	-0.004**	-0.004**	-0.003	-0.003
	(-2.57)	(-2.57)	(-1.63)	(-1.63)
Mkt. Leverage Sup t-1	-0.063***	-0.063***	-0.061***	-0.061***
	(-3.61)	(-3.61)	(-3.13)	(-3.13)
Q Sup t-1 × Mkt. Leverage Sup t-1	-0.026	-0.026	-0.026	-0.026
	(-1.07)	(-1.06)	(-0.97)	(-0.97)
CF/AT Sup t-1	0.063*	0.063*	0.077**	0.077**
	(1.89)	(1.89)	(2.33)	(2.33)
Q Sup t-1 × CF/AT Sup t-1	-0.018	-0.018	-0.025	-0.025
	(-0.97)	(-0.97)	(-1.36)	(-1.36)
Year-Qtr FE	Yes	Yes	No	No
Sup Ind-by-Year-Qtr FE	No	No	Yes	Yes
Cus Ind-by-Year-Qtr FE	No	No	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	98726	98726	93025	93025
R^2	0.725	0.725	0.785	0.785

Table 8: Speed and Supplier-Customer Investment Coordination

Notes: This table presents OLS regression results of the effect of speed of information diffusion on supplier-customer investment coordination. The dependent variable in columns (1) and (2) is the growth in supplier PPE, columns (3) and (4) use supplier CAPX scaled by PPE. The data is organized at the supplier-customer relationship-quarter level. All models include similar supplier control variables as in Table 7, controls for the percentage of sales the customer represents to the supplier and the percentage of cost of goods sold the supplier represents to the customer, their interactions with customer investment as indicated, as well as year-by-quarter and firm-pair fixed effects. Detailed definitions of dependent and independent variables are provided in Appendix A.1. *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.

	PPE Growth Sup		Capx/PPE Sup	
	(1)	(2)	(3)	(4)
Speed	0.002**	0.003**	-0.005	-0.003
	(2.12)	(2.29)	(-1.33)	(-1.03)
PPE Growth Cus	0.028***	0.016		
	(3.66)	(1.37)		
PPE Growth Cus × Speed	0.063***	0.053***		
	(3.23)	(2.79)		
CAPX/PPE Cus			0.110***	0.043*
			(6.88)	(1.69)
CAPX/PPE Cus × Speed			0.056***	0.050***
			(3.65)	(3.43)
Pct of Sales Sup	-0.009	-0.008	0.027**	-0.027
	(-1.20)	(-1.14)	(2.06)	(-1.03)
PPE Growth Cus × Pct of Sales Sup		-0.010		
		(-0.21)		
CAPX/PPE Cus × Pct of Sales Sup				0.260**
				(2.36)
Pct of COGS Cus	0.242***	0.203**	0.199	-0.046
	(3.02)	(2.55)	(1.30)	(-0.23)
PPE Growth Cus × Pct of COGS Cus		1.193***		
		(4.23)		
CAPX/PPE Cus × Pct of COGS Cus				0.939
				(1.62)
Sup Controls	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	90427	90427	96154	96154
R^2	0.340	0.340	0.703	0.703

Table 9: Investment Coordination – Speed and other Information Channels

Notes: This table presents OLS regression results of the effect of speed of information diffusion on supplier-customer investment coordination, analogous to columns (2) and (4) in Table 8. Columns (1) and (2) and columns (3) and (4) respectively split the sample by low and high (above and below median) driving distance, estimated as the required driving time (in hours) from the supplier to the customer headquarter. The dependent variable in columns (1) and (2) is the growth in supplier PPE. In columns (3) and (4) the dependent variable is supplier CAPX, scaled by PPE. The data is organized at the supplier-customer pair-quarter level. All columns include similar supplier control variables as Table 8, as well as year-by-quarter and firm-pair fixed effects. Detailed definitions of dependent and independent variables are provided in Appendix A.1. p-Value (a)-(b) and t-Statistic (a)-(b) summarize the results of a t-test testing if coefficient estimates for $PPE\ Growth\ Cus \times Speed$ in columns (1) and (2) and $CAPX/PPE\ Cus \times Speed$ in columns (3) and (4) are equal, respectively. 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.

	Dep. Var.: PPE Growth Sup		Dep. Var.: Capx/PPE Sup	
	HQ Driving Distance			
	a) Long	b) Short	a) Long	b) Short
	(1)	(2)	(3)	(4)
PPE Growth Cus	-0.014	0.041***		
	(-0.75)	(2.75)		
Speed	0.004**	0.002	-0.009*	0.005
	(2.10)	(1.25)	(-1.67)	(1.11)
PPE Growth Cus × Speed	0.106***	0.004		
	(3.64)	(0.17)		
CAPX/PPE Cus			0.061*	0.028
			(1.68)	(0.80)
CAPX/PPE Cus × Speed			0.076***	0.012
			(3.44)	(0.63)
Pct of Sales Sup	-0.022*	0.004	-0.020	-0.032
	(-1.89)	(0.44)	(-0.56)	(-0.83)
PPE Growth Cus × Pct of Sales Sup	0.015	-0.042		
	(0.20)	(-0.74)		
CAPX/PPE Cus × Pct of Sales Sup			0.211	0.296*
			(1.35)	(1.88)
Pct of COGS Cus	0.302**	0.120	0.055	-0.055
	(2.39)	(1.21)	(0.18)	(-0.22)
PPE Growth Cus × Pct of COGS Cus	1.253***	1.239***		
	(2.99)	(3.28)		
CAPX/PPE Cus × Pct of COGS Cus			0.831	0.968
			(0.94)	(1.26)
Sup Controls	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
p-Value (a)-(b)	.00362		.014	
t-Statistic (a)-(b)	2.69		2.2	
Observations	43619	46263	47177	47962
R^2	.357	.324	.712	.683

Appendix

Table A.1: Variable Definitions and Data Sources

Variable	Short Description	Detailed Comments
R^2 (K lags)	Magnitude of Information Diffusion	Estimated using daily return residuals of the supplier and customer firm (with K lags) in relationship i around the customer's earnings announcement (EA), over the period from 10 days before to 30 days after the EA using the following model, $R_{i,t}^{sup} = \alpha_i + \sum_{k=0}^{K} \beta_{i,k} \times R_{i,t-k}^{cus} + \epsilon_{i,t}$. (Data source: CRSP)
Speed	Speed of Information Diffusion	The ratio of the R^2 ($0\ lags$) over the R^2 ($4\ lags$), scaled to be between 0 and 100, i.e. $Speed = R^2_{\beta_k=0,\forall k\in[1,4]}/R^2 \times 100$. (Data source: CRSP)
Peak Flu NY (PP)	Peak flu incidence in NY region	Indicator variable which takes the value of one if the 'percentage of flu tests with positive results' (PP) is above 20% in the New York region (CDC Region 02) in the given week, and zero otherwise. (Data source: National Respiratory and Enteric Virus Surveillance System (NREVSS))
% Positive	Percentage Positive (PP) Tests	The 'percentage of flu tests with positive results' (PP) in the given week in the given region (i.e. one of the CDC Regtions). (Data source: WHO/NREVSS)
Peak Flu NY (ILI)	Peak flu incidence in NY region	Indicator variable which takes the value of one if the 'percentage of patient visits for influenza like illness symptoms (ILI)' measure is higher than 2% in the New York region (CDC Region 02) in the given week, and zero otherwise. (Data source: Center for Disease Control and Prevention, CDC)
ILI	Influenza-like-Illness	The 'percentage of patient visits for influenza like illness (ILI) symptoms' in the given week in the given region (i.e. one of the CDC regions). (Data source: Center for Disease Control and Prevention, CDC)
Num Dual Analysts	Dual Analyst Coverage	Number of analysts who cover both the supplier and customer firm in the given year, i.e. make at least one EPS forecast for both firms. (Data source: I/B/E/S)
Num Dual Brokers	Dual Brokerage Coverage	Number of brokerage firms who cover both the supplier and customer firm in the given year, i.e. make at least one EPS forecast for both firms. (Data source: I/B/E/S)
Num Cross Owners	Institutional Investor Cross-Ownership	Number of active institutional investors who own at least 5% of the outstanding shares of both the supplier and customer in the given period. (Data source: Factset Lionshares)
Distance	HQ Driving Distance	Driving distance (in hours) from the supplier to the customer headquarter location, as estimated using Google Maps API. (Data Source: Google Maps)
Relationship Length	Customer-supplier relationship duration	Number of years since the supplier-customer link was first reported in Compustat. (Data source: Compustat Segment files)

... continued

Variable	Short Description	Detailed Comments
Pct Sales Sup	Relationship strength	Proportion of total supplier sales represented by sales to the given customer. (Data source: Compustat Segment files)
Pct COGS Cus	Relationship strength	Proportion of total customer cost of goods sold represented by supplier sales to the given customer. (Data source: Compustat Segment files)
Analysts	Analyst Coverage	Number of analysts who issue at least one EPS forecast for the firm in the given year. (Data source: I/B/E/S)
Total Asset	Firm size	Book value of assets (Data source: Compustat)
MCap	Market Capitalization	$\textit{Shares outstanding} \times \textit{stock price}$ (Data source: Compustat & CRSP)
ΔPPE	Investment	(Quarterly) Change in Property, Plants, and Equipment (PPE), scaled by one-period lagged PPE, i.e. $(PPE_{i,t} - PPE_{i,t-1})/PPE_{i,t-1}$. (Data source: Compustat Quarterly)
Capx/PPE	Investment	(Quarterly) Capx, scaled by one-period lagged PPE, i.e. $Capx_{i,t}/PPE_{i,t-1}$ (Data source: Compustat Quarterly)
Q	Tobin's Q	(Quarterly) Tobin's Q following Chen et al. (2007) (CGJ), i.e. $q_{cqj} = (mvq + atq - ceqq)/atq$, where mvq is the market capitalization, atq is the book value of assets, and $ceqq$ is the book value of equity (all quarterly). (Data source: Compustat Quarterly)
PIN	Price Informativeness	Probability of Informed Traded, estimated following Brown and Hillegeist (2007). (Data source: Stephen Brown's website)
1/AT	Inverse Firm Size	$1/\textit{Total Assets (Quarterly)}$ (Data source: Compustat Quarterly)
CF/AT	Cash Flow	$\textit{Cash Flow}/\textit{Total Assets}$ Quarterly cash flow, i.e. income before extraordinary item + depreciation and amortization, scaled by lagged assets. (Data source: Compustat Quarterly)
ROA	Profitability	Quarterly return to assets (%), i.e. net income scaled by asset size. (Data source: Compustat Quarterly)
Inv. Turnover	Sales Turnover	Sales revenue divided by total asset values (%). (Data source: Compustat Quarterly)
$1 - R^2$	Price Informativeness	1 minus the R^2 of a regression of firm i's stock returns on the contemporaneous and one-day lagged market- and industry (Fama-French 10 sectors) returns. (Data source: CRSP and Kenneth French's website).
SUE	Standardized unexpected earnings	Customer firm (Mean quarterly earnings forecast – actual quarterly earnings)/stock price. (Data source: I/B/E/S)
SD(EPS Forecast)	Analyst forecast dispersion	Standard deviation of analysts' earnings forecasts for customer firm. (Data source: I/B/E/S)

Table A.2: Robustness – Alternative Speed Measures

Notes: Analogous to Table 2, this table reports OLS regression estimates, of the speed of supply-chain information diffusion on analyst dual-coverage, broker dual-coverage, and institutional cross-holding. The dependent variable is the speed of information diffusion around customer earnings announcements using returns (*Speed Raw*) in Columns (1)—(3) and residuals from the Fama-French Three Factor model (*Speed FF*3) in Columns (4)—(6). As in Table 2, in Panel A, *Num Dual Analysts* is the number of analysts, *Num Dual Brokers* is the number of brokerage firms, and *Num Cross Owners* is the count of active institutional investors who cross-own the customer and supplier firm in the relationship-quarter. In Panel B, *Dual Analyst* (0/1), *Dual Broker* (0/1), and *Cross Owner* (0/1) are the corresponding dummy variables as in Table 2. We include similar supplier, customer, and earnings announcement (EA) controls as in Table 2. Supplier, customer, and quarterly time-fixed effects are included 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: Continuous measures of analyst dual-coverage and institutional cross-holding

	Speed Raw			Speed (FF3)		
	(1)	(2)	(3)	(4)	(5)	(6)
Num Dual Analysts	0.556***			0.870***		
	(6.19)			(9.71)		
Num Dual Brokers		0.275***			0.339***	
		(4.91)			(6.61)	
Num Cross Owners			0.541***			0.272***
			(5.52)			(3.23)
Supplier, Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier, Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103949	103949	103949	103949	103949	103949
R^2	0.376	0.376	0.376	0.124	0.122	0.122

Panel B: Dummy variables of analyst dual-coverage and institutional cross-holding

	Speed Raw			Speed (FF3)		
	(1)	(2)	(3)	(4)	(5)	(6)
Dual Analyst (0/1)	2.254***			2.067***		
	(5.86)			(6.03)		
Dual Broker (0/1)		1.454***			0.647**	
		(3.84)			(2.11)	
Cross Owner (0/1)			1.336***			0.355
			(4.64)			(1.43)
Supplier, Customer Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier, Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103949	103949	103949	103949	103949	103949
R^2	0.376	0.376	0.376	0.122	0.122	0.122

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

Notes: This table presents the summary statistics of the flu measures across all 10 US HHS regions as provided by the Center for Disease Control and Prevention (CDC) between 1997 and 2014. In Panel A, the flu measure is defined as the "percentage of flu tests with positive results" (PP) collected by WHO/NREVSS Laboratories. Panel B summarizes the measure "influenza-like-illness" (ILI).

Panel A: Percentage positive (PP)

	N	Mean	StDev	p25	Median	p75
01 (New England)	871	8.825	11.606	0.000	2.703	15.524
02 (North East)	885	6.860	8.998	0.170	2.597	11.208
03 (Mid-Atlantic)	877	8.676	12.507	0.000	1.869	14.069
04 (South East)	872	8.609	9.043	1.375	5.275	13.841
05 (Mid-West North)	891	9.516	12.604	0.375	2.848	15.766
06 (South)	872	7.808	10.106	0.635	2.484	12.099
07 (Mid-West South)	889	6.248	9.469	0.000	1.149	9.552
08 (Mountains)	884	7.639	9.858	0.000	2.473	12.788
09 (Pacific South)	885	9.610	10.534	1.569	5.814	14.338
10 (Pacific North)	874	8.884	10.351	0.766	4.734	13.954
Total	8800	8.266	10.630	0.330	3.091	13.233

Panel B: Influenza-like-illness (ILI)

	N	Mean	StDev	p25	Median	p75
01 (New England)	841	0.993	1.035	0.431	0.696	1.195
02 (North East)	841	1.854	1.488	0.966	1.524	2.237
03 (Mid-Atlantic)	841	1.965	1.379	1.092	1.563	2.316
04 (South East)	841	1.749	1.307	0.919	1.305	2.194
05 (Mid-West North)	841	1.641	1.276	0.873	1.232	1.980
06 (South)	841	2.333	1.940	1.128	1.800	3.002
07 (Mid-West South)	841	1.338	1.562	0.470	0.824	1.563
08 (Mountains)	841	1.160	1.159	0.478	0.853	1.403
09 (Pacific South)	841	1.975	1.160	1.134	1.679	2.517
10 (Pacific North)	841	1.675	1.382	0.729	1.335	2.168
Total	8410	1.668	1.442	0.756	1.266	2.089

Table A.4: Robustness – Continuous Flu Measures

Notes: This table, analogous to Table 4, presents results of the interaction effect between flu incidence in the New York (NY) area and analyst/broker dual-coverage on the speed of information diffusion along supply chains. Results based on analyst dual-coverage, broker dual-coverage, and institutional cross-holding are reported in Columns (1), (2), and (3), respectively. The main difference to Table 4 is that this table uses continuous measures of flu incidence in New York (NY). % Positive NY in Panel A is the percentage of positive flu tests in New York in a given week, % ILI NY in Panel B is the percentage of patient visits for influenza-like-illness symptoms in a given week, both from WHO/NREVSS laboratories data. We include similar controls and fixed effects as in Table 4. Detailed definitions of dependent and independent variables are provided in Appendix A.1. *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: Percentage Positive (PP) Tests in NY

	Dependent Variable: Speed		
	(1)	(2)	(3)
Num Dual Analysts	0.975***		
	(10.43)		
Num Dual Brokers		0.408***	
		(7.66)	
Num Cross Owners			0.332***
			(3.43)
% Positive NY	-0.051***	-0.042***	-0.062***
	(-3.67)	(-2.84)	(-4.22)
Num Dual Analysts × % Positive NY	-0.011***		
	(-2.78)		
Num Dual Brokers × % Positive NY		-0.005**	
		(-2.35)	
Num Cross Owners × % Positive NY			0.003
			(0.46)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	99868	99868	99868
R^2	0.131	0.130	0.129

Panel B: Percentage Influenza-like-Illness (ILI) Patient Visits in NY

	Dependent Variable: Speed		
	(1)	(2)	(3)
Num Dual Analysts	0.962***		
	(10.01)		
Num Dual Brokers		0.414***	
		(7.32)	
Num Cross Owners			0.415***
			(3.48)
% ILI NY	-0.144**	-0.077	-0.157**
	(-2.00)	(-1.01)	(-2.08)
Num Dual Analysts × % ILI NY	-0.046*		
	(-1.86)		
Num Dual Brokers × % ILI NY		-0.035***	
		(-2.71)	
Num Cross Owners × % ILI NY			-0.027
			(-0.66)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	96484	96484	96484
R^2	0.131	0.130	0.130

Table A.5: Robustness — Alternative Flu Measure

Notes: This table, analogous to Table 4, presents OLS regressions results of the interaction effect between flu incidence in the New York (NY) area and dual-coverage/cross-holding on the speed of information diffusion along supply chains. This table uses the percentage of influenza-like-illness (ILI) patient visits in NY to measure flu incidence. $PeakFluNY(ILI)$ is a dummy variable that equals one if there is a peak flu episode in the New York area based on the 'percentage of influenza-like-illness (ILI) patient visits' in NY. Similar to Table 4, columns (1), (2), and (3) report results for dual analyst coverage, dual broker coverage, and institutional cross-holding, respectively. 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 A.1. We include supplier, customer, 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: Continuous measures of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed		
	(1)	(2)	(3)
Num Dual Analysts	0.956***		
	(10.37)		
Num Dual Brokers		0.389***	
		(7.25)	
Num Cross Owners			0.373***
			(3.83)
Peak Flu (ILI) NY (0/1)	-0.077	0.116	-0.254
	(-0.28)	(0.40)	(-0.89)
Num Dual Analysts × Peak Flu NY (ILI) (0/1)	-0.249***		
	(-3.13)		
Num Dual Brokers × Peak Flu NY (ILI) (0/1)		-0.120***	
		(-3.05)	
Num Cross Owners × Peak Flu NY (ILI) (0/1)			-0.019
			(-0.16)
Sup./Cus./EA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	96484	96484	96484
R^2	0.131	0.130	0.130

Panel B: Dummy variables of analyst dual-coverage and institutional cross-holding

	Dependent Variable: Speed		
	(1)	(2)	(3)
Dual Analyst (0/1)	2.891***		
	(7.41)		
Dual Broker (0/1)		1.267***	
		(3.66)	
Cross Owner (0/1)			0.340
			(1.17)
Peak Flu (ILI) NY (0/1)	0.188	0.676**	-0.108
	(0.67)	(2.03)	(-0.36)
Dual Analyst × Peak Flu (ILI) NY (0/1)	-1.992***		
	(-4.73)		
Dual Broker × Peak Flu (ILI) NY (0/1)		-1.554***	
		(-4.50)	
Cross Owner × Peak Flu (ILI) NY (0/1)			-0.411
			(-1.17)
Sup./Cus./EA Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	96484	96484	96484
R^2	0.130	0.130	0.129

Table A.6: Robustness – Annual Investment Frequency

Notes: This table summarizes panel regressions of the investment of suppliers on lagged supplier Q and lagged customer Q, and the interaction terms between supplier- and customer Q and the speed measure, analogous to Table 7. The main difference to Table 7 is that the dataset in this table is organized at the pair-year level. For this purpose, the quarterly speed of information diffusion measured around customers' earnings announcements is aggregated at the annual frequency as the mean of the four quarterly speed measures, per supplier-customer pair-year. The measure of supplier firm investment is the change in Property, Plants, and Equipment (PPE) in column (1), CAPX scaled by PPE in column (2), and CAPX + R&D scaled by PPE in column (3). All investment and Q measures are log-transformed to account for outliers. As indicated, we include control variables, interactions with control variables, and fixed effects analogous to Table 7. *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.

	(1) PPE Growth Sup	(2) CAPX/PPE Sup	(3) (CAPX+R&D)/PPE Sup
Speed t-1	0.008	-0.009	0.008
	(0.45)	(-1.08)	(0.42)
Q Sup t-1	0.182***	0.089***	0.067***
	(12.51)	(11.73)	(3.06)
(Q Sup × Speed) t-1	0.036*	0.037***	0.084***
	(1.69)	(3.49)	(2.93)
Q Cus t-1	0.036***	0.026***	0.016
	(3.01)	(3.98)	(0.81)
(Q Cus × Speed) t-1	-0.022	-0.018*	-0.097***
	(-1.01)	(-1.66)	(-3.42)
Controls	Yes	Yes	Yes
Controls × Q Sup	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes
Observations	19199	19109	19109
R^2	0.468	0.682	0.922

Table A.7: Robustness — Dual Coverage and Price Informativeness Controls

Notes: This table summarizes panel regressions analogous to Table 7. Tests in this table include dual analyst coverage interacted with supplier and customer Q in Panel A, and additional measures of price informativeness (supplier and customer PIN and (1-R2) measures) and their interactions with supplier and customer Q in Panel B, respectively. The measure of firm investment is the change in supplier Property, Plants, and Equipment (PPE). All investment and Q measures are log-transformed to account for outliers. The dataset is organized at relationship-quarter level. As indicated, we include similar control variables, interactions with control variables, and fixed effects as in Table 7. *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: Dual coverage

	Dependent Variable: ΔPPE Sup			
	(1)	(2)	(3)	(4)
Q Sup t-1	0.059***	0.055***	0.055***	0.052***
	(18.86)	(13.69)	(16.78)	(12.47)
Q Cus t-1	0.014***	0.010**	0.016***	0.012**
	(3.38)	(2.10)	(3.75)	(2.47)
Dual Analyst (0/1) t-1	-0.001		-0.001	
	(-0.16)		(-0.12)	
(Q Sup × Dual Analyst) t-1	0.009**		0.009**	
	(2.24)		(2.18)	
(Q Cus × Dual Analyst) t-1	-0.011**		-0.011**	
	(-2.31)		(-2.29)	
Dual Broker (0/1) t-1		-0.003		-0.002
		(-0.42)		(-0.34)
(Q Sup × Dual Broker) t-1		0.009**		0.008*
		(2.06)		(1.93)
(Q Cus × Dual Broker) t-1		-0.000		-0.000
		(-0.02)		(-0.02)
Speed t-1			-0.000	-0.000
			(-0.09)	(-0.00)
(Q × Speed) Sup t-1			0.013***	0.013***
			(3.56)	(3.49)
(Q × Speed) Cus t-1			-0.009**	-0.009**
			(-2.23)	(-2.27)
Controls	Yes	Yes	Yes	Yes
Controls × Q Sup	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	64049	64049	64049	64049
R^2	0.355	0.355	0.356	0.356

Panel B: Other price informativeness measures

	Dependent Variable: ΔPPE Sup			
	(1)	(2)	(3)	(4)
Q Sup t-1	0.058***	0.053***	0.060***	0.055***
	(16.02)	(13.90)	(20.30)	(17.70)
PIN Sup t-1	-0.041***	-0.040***		
	(-2.80)	(-2.73)		
(Q × PIN) Sup t-1	0.020	0.018		
	(1.26)	(1.15)		
Q Cus t-1	0.014***	0.016***	0.012***	0.013***
	(3.15)	(3.46)	(3.78)	(3.97)
PIN Cus t-1	-0.007	-0.005		
	(-0.19)	(-0.16)		
(Q × PIN) Cus t-1	0.005	0.004		
	(0.15)	(0.11)		
1-R2 Sup t-1			-0.004***	-0.004***
			(-3.53)	(-3.61)
(Q × 1-R2) Sup t-1			0.002*	0.002*
			(1.71)	(1.83)
1-R2 Cus t-1			0.001	0.002
			(1.01)	(1.04)
(Q × 1-R2) Cus t-1			-0.002	-0.002
			(-1.38)	(-1.39)
Speed t-1		-0.005		-0.004
		(-0.97)		(-1.06)
(Q × Speed) Sup t-1		0.017***		0.014***
		(4.59)		(4.48)
(Q × Speed) Cus t-1		-0.009**		-0.006*
		(-2.22)		(-1.70)
Controls	Yes	Yes	Yes	Yes
Controls × Q Sup	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Observations	63822	63822	94852	94852
R^2	0.385	0.386	0.356	0.357

Table A.8: Robustness – Investment Coordination and Price Informativeness

Notes: This table summarizes panel regressions analogous to Table 8. Tests in this table include additional measures of price informativeness (supplier and customer PIN and (1-R2) measures) and their interactions with customer investment measures. The dependent variable in column (1) is the change in supplier PPE, Column (2) uses supplier CAPX scaled by PPE. Each cell in this table represents a different regression model, i.e. for brevity we report only the coefficient estimate for the interaction of customer investment with supplier or customer price informativeness measure. The dataset for this table is organized at the supplier-customer relationship-quarter level. All models include similar supplier control variables as in Table 8, as well as year-by-quarter and firm-pair fixed effects. Detailed definitions of dependent and independent variables are provided in Appendix A.1. 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.

Augmented Variables	(1) ΔPPE_t^{Sup}		(2) $Capx/PPE_t^{Sup}$
i) $\Delta PPE_t^{Cus} \times PIN_t^{Sup}$	-0.073*	i) $Capx/PPE_t^{Cus} \times PIN_t^{Sup}$	-0.026
	(-1.74)		(-0.96)
ii) $\Delta PPE_t^{Cus} \times PIN_t^{Cus}$	0.008	ii) $Capx/PPE_t^{Cus} \times PIN_t^{Cus}$	0.171***
	(0.09)		(3.38)
iii) $\Delta PPE_t^{Cus} \times (1-R^2)_t^{Sup}$	-0.007**	iii) $Capx/PPE_t^{Cus} \times (1-R^2)_t^{Sup}$	-0.003*
	(-2.08)		(-1.70)
iv) $\Delta PPE_t^{Cus} \times (1-R^2)_t^{Cus}$	-0.002	iv) $Capx/PPE_t^{Cus} \times (1-R^2)_t^{Cus}$	0.003
	(-0.38)		(1.40)

Table A.9: Information Sharing Channels and the Speed of Information Diffusion

Notes: This table reports OLS regressions analogous to those reported in Table 2. The following variables, representing private information channels, are added to the specification reported in Column (4) of Table 2: *HQ Driving Distance* (h) measures the estimated driving time for the supplier's to the customer's headquarter location (in hours), according to the Google Maps API. *Relationship Duration* is the number of quarters since the supplier-customer relationship was initiated. Similar to Table 2, *Num Dual Analysts* is the number of analysts simultaneously covering both the customer and the supplier in the relationship-quarter. $NumofCrossOwners$ is the number of active institutional investors holding at least 5% of outstanding shares of both the customer and the supplier firms in the relationship-quarter. All other control variables and fixed effects are similar to Column (4) of Table 2. 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.

	Dependent Variable: Speed	
	(1)	(2)
HQ Driving Distance (h)	-0.007	
	(-0.68)	
Relationship Length		0.001
		(0.03)
Num Dual Analysts	1.078***	0.998***
	(11.16)	(11.57)
Num Cross Owners	0.325***	0.365***
	(3.84)	(4.61)
Sup. Controls	Yes	Yes
Cus. Controls	Yes	Yes
EA Controls	Yes	Yes
Year-Qtr FE	Yes	Yes
Supplier FE	Yes	Yes
Observations	89466	104026
R^2	0.109	0.113