Volatility Information Transfer along the Supply Chain: Evidence from Corporate Disclosures[1]

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Abstract

We study how new information about a firm's future volatility affects market expectation of its suppliers' volatility, using a measure based on the change of option-implied forward volatility around corporate disclosure events. We show analytically and empirically that the change of forward volatility is an unbiased measure of new volatility-related information. Our analysis identifies a positive volatility information transfer (VIT) effect from customers' public disclosures to suppliers. Customers' unbundled management guidance generates a stronger VIT effect than their earnings announcement. The VIT effect is stronger if customers are larger, have more suppliers, or have a stronger economic link with suppliers.

Keywords: Customer-to-supplier information transfer, Management guidance, Model-free implied volatility, Earnings announcement, Supply-chain relationship

JEL Classification: G12, G13, G14, G17

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Volatility Information Transfer along the Supply Chain: Evidence from Corporate Disclosures

1 Introduction

Stock price volatility is of great interest to institutional investors, derivative traders, corporate management, regulators, and researchers, because it plays a critical role in equity valuation, stock option pricing models, investment risk management, corporate financial planning, and so on. Prior studies show that firm-level volatility is related to economic fundamentals such as GDP growth and industry output (Campbell et al., 2001), earnings volatility (Wei and Zhang 2006), growth option (Cao, Simin, and Zhao, 2008), sales and cash flow variability (Irvine and Pontiff 2009), as well as non-fundamental factors such as corporate disclosure practices and institutional ownership (Bushee and Noe, 2000; Xu and Malkiel, 2003) and retail trading (Brandt et al., 2010; Foucault, Sraer, and Thesmar, 2011). In a recent theory paper, Herskovic, Kelly, Lustig, and Van Nieuwerburgh (hereafter, HKLV 2020) demonstrate that firm-specific uncertainty shocks can propagate through the production network as a firm's growth rate is closely related to its suppliers' growth rates. The theory of HKLV (2020) suggests that new information about a firm's future volatility can have a spillover effect on market expectation of its suppliers' volatility. However, there is lack of empirical evidence on how new information about one firm's future volatility is transferred to other related firms. We attempt to fill in this void of the literature.

Corporate disclosures release new information that can prompt investors to update their expectation of firm growth and future cash flows (Verrecchia, 1983). While new information typically reduces the uncertainty about future firm performance, information that differs significantly from consensus expectation can cause a net increase in the expected volatility of future stock return (Lewellen and Shanken, 2002; Pastor and Veronesi, 2009; Neururer, Papadakis, and Riedl, 2016). Patell and Wolfson (1979, 1981) show that option implied volatility tends to drop sharply after earnings announcements. Rogers, Skinner, and Van Buskirk (2009) report evidence that option implied volatility increases after the release of management earnings guidance that is unbundled with earnings announcement. One common interpretation of the change in option implied volatility after a firm's public disclosure is that option traders revise their expectation of the firm's future volatility in response to newly disclosed information.

However, recent studies point out that the change of a firm's option implied volatility after its earnings announcement may be a biased measure of new information about the firm's future volatility (Dubinsky et al., 2019; Smith and So, 2022). Their argument is built on the observation that quarterly earnings announcement is often pre-scheduled and investors know the earnings announcement date in advance but do not know the actual earnings that is to be released on the announcement day. The uncertainty about the actual earnings before its release causes option traders to increase the expected volatility of the announcement day stock return, which leads to a significant increase in option implied volatility in days leading up to earnings announcement. Because the earnings announcement risk disappears right after the release of actual earnings, it results in a negative change of implied volatility after earnings announcement that is unrelated to the firm's future volatility. We provide corroborating evidence on the effect of the earnings announcement risk by comparing two different types of public disclosures, the mandatory quarterly earnings announcement (QEA) versus the voluntary management guidance (MG) that is unbundled with earnings announcements. Since the date of an unbundled MG is not known to investors in advance, the option implied volatility before an unbundled MG is not raised up by the earnings announcement risk. In fact, we find that the short-term implied volatility decreases by 11.3% on average after QEA events in our sample but increases by 3.2% on average after unbundled MG events in our sample.[1]

Since new information in a firm's public disclosure is unexpected and may result in upward or downward revision of market expectations of the firm's future volatility, an unbiased measure of new information about the firm's future volatility should have a probability distribution that centers at zero. In this study, we construct one measure of new volatility information based on the change of forward volatility (i.e., the expected volatility of the stock return in a time window in the future). We show analytically in Section 2 that the change of short-term expected volatility around earnings announcement is subject to the negative bias caused by the earnings announcement risk, but the change of forward volatility is free of this bias. Empirically, we find that the average change of option-implied forward volatility is close to zero, for instance, only 0.30% after QEA events. In addition, our regression analysis shows that the change of forward volatility after a firm's QEA is positively and significantly related to the firm's realized volatility in the future; in contrast, the change of short-term implied volatility has no significant relationship with the realized volatility after controlling for the change of forward volatility. The results suggest that forward volatility is informative about a

[1] Many studies in the literature examine the information content of accounting earnings and earnings announcements; see, e.g., Amin and Lee (1997), Billings and Jennings (2011), Barth and So (2014), and the references in the review article by Kothari and Wasley (2019). Management guidance constitutes an important channel of voluntary disclosure through which managers communicate with market participants and have been the subject of numerous studies in the past decades (see the review by Healy and Palepu, 2001; Hirst, Koonce, and Venkataraman, 2008; Leuz and Wysocki, 2016; and the references therein). In particular, management earnings guidance accelerates the timing and increases the frequency of disclosure about a firm's fundamental information. Prior research has shown that unexpected disclosures about earnings-related information likely cause investors to revise their evaluation of a firm, potentially increasing uncertainty about the underlying firm value (e.g., Hutton, Miller, and Skinner, 2003; Rogers, 2008).

firm's future volatility and the change of forward volatility is a better proxy of new volatility information than the change of short-term implied volatility.

We develop our hypotheses about the volatility information transfer effect along the supply chain based on the production network model of HKLV (2020). In an economy that features production networks, firm performance is related to shocks to the other firms that are economically linked through production activities. Large firms and firms with extensive connections in the production network aggregate production information from a large number of sources. The theory of HKLV (2020) predicts that the announcing firm (hereafter, the announcer)'s size and the number of its suppliers both have a positive influence on the strength of volatility information transfer to its suppliers. In addition, direct economic links between the announcer and its supplier, such as the sales to the announcer as a fraction of the supplier's total sales and the duration of their customer-supplier relationship, can positively affect the strength of volatility information transfer.

The task of empirically identifying the VIT effect from customers to suppliers is challenging for several reasons. First, the strength of production links between a customer and its suppliers varies substantially. For example, the average duration of the customer-supplier relationship that had existed before the customer's QEA events in our sample is eight calendar quarters (i.e., two years) and the fifth and 95th percentiles of the relationship duration are one and 39 quarters respectively. It is hard to find the VIT effect if the customer-supplier relationship is new because investors are not certain about the implications of the customer's disclosed information on the suppliers' future performance. Second, several studies find that there exists a strong factor structure in the cross-sectional variation of firm-level volatilities. For example, Engle and Figlewski (2015) and Christoffersen, Fournier, and Jacobs (2018) examine daily option implied volatilities for large cap stocks and document strong evidence that one market-wide factor has a strong explanatory power of cross-sectional variation in firm-level volatilities. Herskovic et al. (2016) find that a single common factor explains about one-third of the variation in idiosyncratic volatility for equity shares in the CRSP database. In view of these findings, volatility comovement between a customer and its supplier around the customer's public disclosure could be driven by the contemporaneous change of the market-wide factor. Third, it is well documented that there exists the stock return spillover effect along the supply chain, that is, a firm's disclosure causes the change of its supplier's stock price (Cohen and Frazzini, 2008; Pandit, Wasley, and Zach, 2011; Cheng and Eshleman, 2014). The leverage effect (Black, 1976) suggests that the change of a firm's volatility is negatively correlated with its own return, and the return spillover from the announcer to its supplier can lead to the change of the supplier's implied volatility. We control for the influence of the market-wide factor and the return spillover effect in our regression model to increase the power of identifying the VIT effect across individual firms.

For our empirical analysis, we obtain customer-supplier pairs from the FactSet Revere Supply Chain database, which collects information about customer-supplier relationships from many sources and provides an extensive coverage of supply-chain relationships of publicly listed firms, private firms, and government entities since 2003 (Gofman, Segal, and Wu, 2020). For firms that are identified as customers in the database, we collect their quarterly earnings announcements (QEA) dates from the Compustat database and their management guidance (MG) dates from the Thomson Reuters IBES Guidance database. An event in our study refers to a unique pair of a customer's disclosure date and one of its suppliers. We construct two samples of events: one sample of 190,325 QEA events and the other sample of 64,116 MG events that are unbundled with earnings announcements. We analyze QEA and MG events separately as they are the most common types of mandatory and voluntary disclosures, respectively. Earnings announcements are regularly released on dates that are often highly anticipated, which draw investors' attention and prompt them to trade strategically ahead of the announcement dates (Levi and Zhang, 2015; Johnson and So, 2018; Liu et al., 2020). On the other hand, firms have the flexibility to decide whether and when to issue voluntary disclosures. While firms tend to issue management guidance concurrently with quarterly earnings announcements in recent years (Rogers and Van Buskirk, 2013), the timing of unbundled management guidance is sporadic and unexpected.

To calculate the change of forward volatility around event dates as a proxy for new volatility information, we use prices of single stock options in the OptionMetrics database and apply the model free implied volatility (MFIV) method. MFIV is free of the errors caused by misspecification of an option pricing model. It is more informative than the Black-Scholes model implied volatility because MFIV is derived from multiple option prices across a wide range of strike prices (Jiang and Tian, 2005).

Our regression results show a positive VIT effect from the announcing customers to their suppliers. For the sample of QEA events, an increase of 100 basis points (bps) in a customer's forward volatility is associated with a 2.6 bps increase in its supplier's forward volatility. The VIT effect is much stronger for the sample of MG events – a 100 bps increase in a customer's forward volatility is associated with a 5.1 bps increase in its supplier's forward volatility. Moreover, there exists significant cross-sectional variation in the VIT effect from customers to suppliers. For example, in response to a 100 bps increase in the customer's forward volatility after an unbundled management guidance, its supplier's forward volatility increases by 12.0

bps if the customer's firm size is in the top tercile, but only 1.9 bps if the customer's firm size is in the bottom tercile. For the same 100 bps increase in the customer's forward volatility after an unbundled management guidance, its supplier's forward volatility increases by 7.4 bps if sales to the customer accounts for more than 15% of the supplier's total annual sales, but only 2.9 bps if sales to the customer accounts for less than 15% of the supplier's total annual sales. The results suggest that investors revise their expectation of a supplier's volatility to incorporate new information upon its customer's corporate disclosures in a manner that reflects the customer's role in the production network and the strength of the economic link between the two firms.

Our study is related to several streams of the literature. First, our study contributes to the literature concerning how a firm's new information release affects other firms. Prior studies on information transfer focus on the stock return spillover effect, i.e., the impact of the public disclosure on related firms' stock price (e.g., Foster, 1981; Freeman and Tse, 1992; Pandit, Wasley, and Zach, 2011). Few studies examine volatility information transfer across firms. To the best of our knowledge, Hann, Kim, and Zheng (2019) is the only published study that examines the VIT effect across individual firms in the same industry. They identify the first announcer of quarterly earnings in an industry and examine how the first announcer's earnings announcement affects the option implied volatility of peer firms in the same industry. The major differences between our study and theirs include the following. One, we analyze the VIT effect along the supply chain, as customers and suppliers have strong economic links via sales contracts and suppliers are inherently responsive to uncertainty shocks about customers. Two, their study focuses on only QEA events, whereas we study both QEA and MG events. We find strong differences in the VIT effect between two types of disclosures. Third, we use the change of forward volatility after a public disclosure to capture the new volatility information while their study mainly focuses on the change of constant-maturity implied volatility.[2]

Second, our study contributes to a better understanding of volatility comovement between firms. While recent studies find that firm-level volatilities are highly correlated (Engle and Figlewski, 2015; Herskovic et al., 2016; Christoffersen, Fournier, and Jacobs, 2018), it is unclear why the volatilities of individual firms co-move with each other. The theory of HKLV (2020) suggests that volatility comovement is related to production links between firms, which has implications of the cross-sectional variation in the strength of volatility information transfer across firms. The empirical results from our study are consistent with the production network explanation of volatility comovement.

Third, we make an incremental methodological contribution on how to quantify new information about a firm's future volatility after the firm makes a public disclosure. We demonstrate analytically and empirically that the change of option-implied forward volatility is an unbiased measure of new volatility information. Our measure is related to the information measure in Smith and So (2022) but differs in several key aspects. One, our measure is based on the change of option-implied forward volatility around a public disclosure. Smith and So's measure is based on the change of constant-maturity implied volatility around a public disclosure. The maturity terms of constant-maturity implied volatilities before and after the disclosure do not completely overlap as the maturity term after the disclosure covers a few days

[2] In additional analysis, we follow the approach in Hann, Kim, and Zheng (2019) to construct a sample of the first announcers and their industry peers and examine how the change of the first announcers' forward volatility around their announcement dates is related to the change of their industry peers' forward volatility. Our empirical results support a positive VIT effect from the first announcers to their industry peers, although the industry peer effect appears less significant than the effect from customers to suppliers. The empirical results are available upon request.

that are not included in the maturity term before the disclosure. Two, since the change of short-term constant-maturity implied volatility after quarterly earnings announcements is biased downward due to the earnings announcement risk, Smith and So correct the bias by using one long-maturity and one short-maturity implied volatility before the announcement to quantify the bias. Our measure does not require such a bias correction because the change of forward volatility is not affected by the earnings announcement risk.[3] Third, our measure can be applied to study both anticipated (e.g., quarterly earnings announcement) and unanticipated (e.g., unbundled management guidance) disclosure events. Since the earnings announcement risk does not occur in unanticipated disclosure events, the bias correction term in Smith and So's measure is likely to introduce additional noise in capturing new volatility information.[4]

The remainder of the paper is organized as follows. Section 2 presents an analysis of the change of expected variances around a public disclosure event and our research hypotheses. Section 3 discusses data and our sample. Section 4 presents preliminary empirical results on the change of implied volatilities around disclosure events. Section 5 reports empirical results for testing the effect of volatility information transfer across firms. Section 6 concludes.

2 Hypothesis Development

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[3] Smith and So's measure captures the change in implied volatility over the period between the announcement date and a future date. Given the values of their measure for two future dates, say, day T_1 and T_2 (here $T_2 > T_1$), it is possible to use the difference between the T_2 value and the T_1 value of their measure as a proxy for the change in forward volatility between day $T_1 + 1$ and T_2, which is conceptually similar to our measure. However, the misalignment in the maturity terms of the constant-maturity implied volatilities that are used in the calculation of their measure may reduce the effectiveness of using the difference between the T_2 and T_1 values of their measure to quantify new volatility information.

[4] Smith and So (2022) state that "… the key innovation of our approach is that it embeds an expectation model about the anticipated arrival of information that is less likely effective in cases where investors do not anticipate an impending information release." (p. 411)

2.1 Mathematical Analysis of the Change in Expected Variance around an Event Date

To build the foundation for developing our hypotheses, we define the expected stock return variances around an event date in mathematical terms and study how a public disclosure may affect these expected variances. Suppose that one firm announces earnings on day *t*. Let $\sigma^2_{t,T}$ be the expected variance of the stock return between day *t+1* and day *T* inclusively, conditional on the public information set at the end of day *t*. It can be expressed mathematically in the discrete-time form as follows,

$$\sigma^2_{t,T} = \frac{1}{T-t} \sum_{u=t+1}^{T} \sigma^2_{u|t} \qquad (1)$$

where $\sigma^2_{u|t}$ is the expected variance on day *u* conditional on the day *t* information set. Note that all $\sigma^2_{u|t}$ are measured at the end of day *t* and expressed in the annual rate.

The announcement on day *t* may have an impact on short-term and long-term expected variances. We define the short-term expected variance σ^2_{t,T_1} as the expected variance of stock returns between day *t+1* and day T_1, and the long-term expected variance σ^2_{t,T_2} as the expected variance of stock returns between day *t+1* and day T_2. Both T_1 and T_2 are fixed and larger than *t*, and T_2 is larger than T_1. The change of the short-term expected variance from day *t-1* to day *t* is represented by $\sigma^2_{t,T_1} - \sigma^2_{t-1,T_1}$, and the change of the long-term expected variance from day *t-1* to day *t* is represented by $\sigma^2_{t,T_2} - \sigma^2_{t-1,T_2}$.

In addition, we define the forward variance FV_{t,T_1,T_2} as the expected variance of the stock return between day T_1+1 and day T_2 inclusively, conditional on the day *t* information set. It can be expressed mathematically in the discrete-time form as follows

$$FV_{t,T_1,T_2} = \frac{1}{T_2 - T_1} \sum_{u=T_1+1}^{T_2} \sigma_{u|t}^2. \qquad (2)$$

It can be seen that $\sigma_{t,T}^2 = FV_{t,t,T}$. The change of the forward variance from day *t-1* to day *t* is represented by $FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}$.

Given the above definitions, we can prove the following mathematical relation between the changes of the long-term, short-term, and forward variances. The details of our proof are provided in Appendix A.

$$\sigma_{t,T_2}^2 - \sigma_{t-1,T_2}^2 = \left(\frac{T_1 - t}{T_2 - t}\right)\left[\sigma_{t,T_1}^2 - \sigma_{t-1,T_1}^2\right] + \left(\frac{T_2 - T_1}{T_2 - t}\right)\left[FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}\right]$$
$$+ \left(\frac{1}{T_2 - t}\right)\left[\sigma_{t-1,T_2}^2 - \sigma_{t-1,T_1}^2\right]. \qquad (3)$$

Equation (3) shows that the change of the long-term expected variance from day *t-1* to day *t* is the sum of three components – the change of the short-term expected variance, the change of the forward variance, and an adjustment term that has a relatively small magnitude and is not affected by new information on the announcement day *t*. In the next subsections, we discuss the impact of a public disclosure on each of the three components respectively and formulate our research hypotheses.

2.2 Impact of a Public Disclosure on Expected Variances

The first component on the right-hand side of Equation (3), $\left(\frac{T_1-t}{T_2-t}\right)\left[\sigma_{t,T_1}^2 - \sigma_{t-1,T_1}^2\right]$, captures the impact of a public disclosure on the short-term expected variance. It is important to note that whether or not the date of a public disclosure is scheduled and known to the public in advance has a significant effect on the change of the short-term expected variance $\sigma_{t,T_1}^2 -$

σ^2_{t-1,T_1}. Quarterly earnings announcements are mandatory and regular disclosures. Investors pay close attention to the upcoming earnings announcements and often know the announcement dates in advance. On the other hand, management guidance is voluntary and does not have to follow a pre-determined schedule. In recent years, firms often release management guidance concurrently with earnings announcements. In the following discussions and empirical analysis, we focus on *unbundled* management guidance, for which the announcement date is typically unscheduled and unanticipated by investors.

On the day before a quarterly earnings announcement (i.e., day *t-1*), because of the uncertainty about the actual earnings and the stock price movement in response to earnings surprise, the value of $\sigma^2_{t|t-1}$ is higher than the value of $\sigma^2_{u|t-1}$ for $t+1 \leq u \leq T_1$.[5] Note that according to Equation (1), $\sigma^2_{t|t-1}$ is included in σ^2_{t-1,T_1} (the short-term expected variance on day *t-1*), but not in σ^2_{t,T_1} (the short-term expected variance on day *t*). Thus, the change of the short-term expected variance $\sigma^2_{t,T_1} - \sigma^2_{t-1,T_1}$ is expected to take a negative value. Because the negative value is caused by the elevated value of $\sigma^2_{t|t-1}$ and not related to the firm's future volatility after day *t*, the change of the short-term expected variance is a contaminated measure of the new information about the firm's future volatility and contains a negative bias.

In contrast, an unbundled management guidance attracts investors' attention only after the guidance is released to the public. On the day before an unbundled management guidance (i.e., day *t-1*), investors do not know there will be a management guidance on day *t*, hence the value of $\sigma^2_{t|t-1}$ is not elevated before the event. Therefore, unlike the change of short-term

[5] Other studies including Levi and Zhang (2015) and Johnson and So (2018) find that liquidity traders and market dealers are less willing to trade before earnings announcement because of the high level of information asymmetry, which also increases the value of $\sigma^2_{t|t-1}$.

expected variance around a quarterly earnings announcement, the change of short-term expected variance around an unbundled management guidance does not contain a negative bias.

The second component on the right-hand side of Equation (3), $\left(\frac{T_2-T_1}{T_2-t}\right)\left[FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}\right]$, is not affected by whether investors know the date of a public disclosure in advance. The change of the forward variance from day *t-1* to day *t*, $\mathrm{FV}_{\mathrm{t,T_1,T_2}} - \mathrm{FV}_{\mathrm{t-1,T_1,T_2}}$ represents the revision of market expectation of the return volatility between day $T_1 + 1$ and day T_2 upon the arrival of new information on the announcement day *t*. Since neither $\mathrm{FV}_{\mathrm{t,T_1,T_2}}$ nor $\mathrm{FV}_{\mathrm{t-1,T_1,T_2}}$ contains $\sigma^2_{t|t-1}$, the change of the forward variance $\mathrm{FV}_{\mathrm{t,T_1,T_2}} - \mathrm{FV}_{\mathrm{t-1,T_1,T_2}}$ is not affected by the value of $\sigma^2_{t|t-1}$ and thus an unbiased measure of the new information about the firm's future volatility. Moreover, since new information on the announcement day *t* is random and unpredictable, the expected value of $\mathrm{FV}_{\mathrm{t,T_1,T_2}} - \mathrm{FV}_{\mathrm{t-1,T_1,T_2}}$ is equal to zero conditional on day *t-1* information.

As for the third component on the right-hand side of Equation (3), $\left(\frac{1}{T_2-t}\right)\left[\sigma^2_{t-1,T_2} - \sigma^2_{t-1,T_1}\right]$, because both σ^2_{t-1,T_2} and σ^2_{t-1,T_1} represent the pre-announcement expected variance, it does not capture the new information that is released on day *t*. Moreover, since the weight $\frac{1}{T_2-t}$ is much smaller than the weights of the first two components $\frac{T_1-t}{T_2-t}$ and $\frac{T_2-T_1}{T_2-t}$, the third component is a very small part of the change of the long-term expected variance $\sigma^2_{t,T_2} - \sigma^2_{t-1,T_2}$.

In summary, the above discussions suggest that the change of the short-term (and long-term) expected variance is negatively biased around *prescheduled* earnings announcements, but not around *unbundled* management guidance.[6] More importantly, for both types of disclosure events, the change of the forward variance is not subject to the bias associated with the uncertainty about the announcement day stock price.

2.3 Hypotheses

Based on the above analysis and discussions, it is natural to consider using the change of the forward variance as an empirical proxy for new information about the firm's future volatility. Since new information contained in corporate disclosures is unpredictable, it may have either a positive or negative impact on the forward variance; thus, we expect that the distribution of the change of the forward variance center at zero. To empirically test the unbiasedness property of the change of the forward variance, we state our first hypothesis as follows.

Hypothesis 1: The change of the announcer's forward variance around a disclosure event has an expected value equal to zero, regardless of whether the event is pre-scheduled or unscheduled.

After we establish that the change of the forward variance is an unbiased measure of new volatility information, we can use it to examine how the new volatility information is transferred across firms along the supply chain. According to the theory of HKLV (2020), customers and suppliers are economically linked via production network and a customer's

[6] Prior studies in the literature have documented that the implied volatility of short-term equity options, on average, decreases sharply after earnings announcements (Patell and Wolfson, 1979, 1981; Donders and Vorst, 1996; Isakov and Perignon, 2001; Ni, Pan, and Poteshman, 2008; Hann, Kim, and Zheng, 2019). In contrast, in a study of unbundled management guidance, Rogers, Skinner, and Van Buskirk (2009) find that short-term implied volatility increases after the release of management guidance.

growth rate is closely related to its supplier's growth rate. Thus, new volatility information in a customer's disclosure is likely to cause a change of investors expectation of its suppliers' future volatility. This *volatility information transfer* (VIT) effect is the focus of our study. To empirically investigate the VIT effect, we state the second hypothesis as follows.

Hypothesis 2: After controlling for the contemporaneous changes of the market-wide volatility and the event-window stock returns, the change of a firm's forward variance around its public disclosure has a positive effect on the contemporaneous change of its supplier's forward variance.

Moreover, the production network theory of HKLV (2020) suggests that the importance of a customer-supplier link depends on the size of the customer. Shocks to large firms are likely to have a significant impact on their suppliers, leading to a strong VIT effect from customers to suppliers. Another firm characteristic that may be related to the VIT effect is the number of suppliers, as firms that have extensive connections in the network aggregate more production information. In addition, we expect that the stronger the economic relationship between the announcing customer and its supplier, the stronger the VIT effect. The strength of economic relationship can be measured by the sales to a customer as a fraction of the supplier's total sales and the duration of a customer-supplier relationship. The VIT effect is weaker in newly established customer-supplier pairs because the relationship may be tenuous and investors are not certain about the implications of the customer's disclosed information on the suppliers. Hence, we have the third hypothesis as follows.

Hypothesis 3: The VIT effect from a firm to its supplier is stronger if the announcer is larger, has a greater number of suppliers, or a stronger economic relationship with the supplier.

3 Data and Estimation Methodology

3.1 Samples of Corporate Disclosure Events

We use the FactSet Revere Supply Chain database to identify the customer-supplier pairs and merge the FactSet Revere database, the CRSP/Compustat Merged database, the OptionMetrics database, and the Thomson Reuters IBES Guidance database together. We obtain financial statement data from Compustat, historical stock prices and returns from CRSP, and the equity option data from the OptionMetrics database. The FactSet Revere database collects information about customer-supplier relationships from many sources and provides an extensive coverage of supply-chain relationships of publicly listed firms, private firms, and government entities since April 2003. Each customer-supplier relationship in the database exists continuously between a start date and an end date. We take a snapshot of the database at the end of each calendar quarter between June 2003 and December 2020 inclusively to identify the customer-supplier relationships that existed at the time point and assume that the relationships continued in the following quarter.

Table I presents the major steps of the procedure we follow to select the sample of corporate disclosure events for empirical analysis. Earnings announcement dates are usually pre-determined while unbundled management guidance dates are not. Panel A of Table I shows the procedure of selecting our sample of quarterly earnings announcements (QEA) events. We collect the QEA dates from the Compustat database. A firm may have more than one supplier. A QEA event refers to one unique pair of a firm's QEA date and one of its suppliers. The initial sample that we obtained by merging the above-mentioned databases includes a large number of 475,614 QEA events. To avoid the confounding effect of a supplier's own earnings announcement, we exclude an event from our sample if the supplier's own earnings announcement falls between the five days before and the ten days after its customer's announcement. After removal of overlapping events with suppliers' own earnings announcements, 298,957 events remain in the sample. Next, we remove the events if either the announcing customer or its supplier is in banking, financial institutions, and utilities industry according to the Fama-French 48-industry classification. We also follow prior studies to exclude an event if either the supplier's or the customer's stock price before the QEA date was below $5. In the last step, we remove the observations with extreme values beyond 0.1% at each end of the distribution of the continuous variables that are used in the regression analysis and described in Section 4. The final sample in Panel A includes 190,325 QEA events.

[Table I is about here]

Panel B of Table I shows how we select the sample of unbundled management guidance (MG) events. We collect the MG dates from the IBES Guidance database. If the database includes more than one MG record of the same firm on the same date, we count the date only once for that firm. We include only the dates on which the firm issued either earnings guidance or sales guidance.[7] A MG event refers to one unique pair of a customer's MG date and one of its suppliers. The selection procedure in Panel B is similar to that in Panel A, with only one additional step in which we remove the MG events that occurred on the same day as the

[7] The theory of HKLV (2020) also applies to sales guidance because, just like earnings information, new sales information generates volatility shocks, which is propagated through supply chain network. Thus, we include both earnings and sales guidance in our sample of management guidance events.

announcer's QEAs. This step is necessary because the purpose of analyzing the sample of MG events is to study how volatility shocks caused by unscheduled corporate disclosures are transmitted across firms. Keeping the MG events that are bundled with earnings announcements defeats this purpose. We observe in Panel B that the number of MG events in our sample drops from 268,373 to 88,563 after the bundled MG events are removed. The final sample in Panel B includes 64,116 MG events.

3.2 Estimation of the Expected Stock Return Variances

We estimate the expected stock return variance using the model-free estimation approach, which produces model-free implied variances based on the prices of exchange-traded stock options and is not subject to the restrictive assumptions of the underlying stock price dynamics that the commonly used Black-Scholes option pricing model requires.[8] The model-free implied variance (MFIV) is constructed as a portfolio of out-of-the-money call options and put options on the underlying stock and can be expressed mathematically as follows:

$$MFIV_{t,T} = \frac{2e^{r(T-t)}}{T-t}\left(\int_0^{F_{t,T}} \frac{P_t(K,T)}{K^2}dK + \int_{F_{t,T}}^{\infty} \frac{C_t(K,T)}{K^2}dK\right), \qquad (4)$$

where *r* is the risk free interest rate and is assumed to be constant between day *t* and day T, $F_{t,T}$ is the forward price of the underlying stock on day *t*, and $C_t(K,T)$ and $P_t(K,T)$ are prices of European call and put options with strike price *K* and maturity day *T*, respectively.[9] To improve

[8] The model-free implied variance measures the expected return variance under the risk-neutral probability, i.e., the expected return variance under the actual probability plus risk premium (Figlewski, 2018). In the standard option price model, the risk premium is specified as an increasing and affine function of variance, i.e., the risk premium increases in variance linearly. Thus, using the risk-neutral expected variance does not affect the interpretation of information transfer of the expected variance in the actual probability.

[9] Britten-Jones and Neuberger (2000) show that under the assumption that the underlying asset price follows a diffusive process, $MFIV_{t,T}$ is equal to the risk-neutral expected variance from *t* to *T*. Jiang and Tian (2005) and

the quality of numerical integration in the calculation, we follow the approach in Jiang and Tian (2005) to implement an interpolation–extrapolation technique across moneyness from 1% to 300%. We use the implied variances in the OptionMetrics database that are computed with a proprietary algorithm for future dividends estimation and a binomial tree approach to account for the early exercise premium. For each maturity, we interpolate implied variances from out-of-the-money call and put options with available strike prices, using a cubic spline. For moneyness levels below (above) the available strike prices, we simply extrapolate the implied variance of the lowest (highest) available strike price. We calculate the option prices using the Black-Scholes formula from the interpolated/extrapolated variances and estimate the MFIV for each maturity of available options. Finally, for any maturity that does not have available options, we linearly interpolate the MFIVs at the two adjacent maturities, one being longer than the other, to estimate the MFIV of that maturity.

In our empirical analysis, we estimate the short-term expected variance σ^2_{t,T_1} by $MFIV_{t,T_1}$, the long-term expected variance σ^2_{t,T_2} by $MFIV_{t,T_2}$, and the forward variance FV_{t,T_1,T_2} by $\left(\frac{1}{T_2-T_1}\right)\left[(T_2-t)MFIV_{t,T_2}-(T_1-t)MFIV_{t,T_1}\right]$. To isolate the effect of the elevated event-day expected variance without reducing the information content in the forward variance, we select a large value of T_2 and a small value of T_1. We choose $T_2 - t$ to be 182 calendar days (about 6 months). Stock options with a longer than 6-month maturity tend to be less liquid, and some stocks do not even have long-maturity options. To avoid the microstructure issues of extreme

Carr and Wu (2009) show that the results hold approximately even if the underlying asset price follows a more general process with jumps.

short-maturity options, we choose $T_1 - t$ to be 20 calendar days.[10] As illustrated in Figure 1, we obtain the short-term (20-day) implied variance for the period that ends on the 20th calendar day after announcement, the long-term (6-month) implied variance for the period that ends on the 182nd calendar day after announcement, and the forward implied variance for the period between the 21st and 182nd day after announcement inclusively.

[Figure 1 is about here]

4 Change of Implied Volatilities around Disclosure Events

4.1 Descriptive Statistics

This section presents empirical evidence on the change of the implied volatilities around corporate disclosure events. For each disclosure event date (day 0), the pre-event window includes day -2 and day -1, and the post-event window includes day 1 and day 2. We do not include day 0 in either pre- or post-event window because the disclosure may be released at any time within a day – before market opening in the morning, during or after trading hours. For each day in the pre- or post-event window, we follow the method described in Section 3 to calculate the 20-day implied variance and the forward implied variance. We define the pre-event (post-event) implied volatility (in short, IV) as the square root of the average implied variance over the days in the pre-event (post-event) window. We then calculate the change in a firm's 20-day (forward) IV around the disclosure event as the logarithm of the firm's post-event 20-day (forward) IV minus the logarithm of the firm's pre-event 20-day (forward) IV.

[10] It is a common practice in the literature to exclude extreme short-maturity options from empirical analysis due to liquidity issues. We remove the options with maturities less than seven calendar days in our study.

Our first hypothesis implies that the average change in the announcer's forward IV is close to zero for both QEA and MG samples.

We examine descriptive statistics on the announcers' IV changes around QEA and MG events in Panel A of Table II. There exists a sharp difference in the change of the 20-day IV between QEA and MG events: the mean (median) of the 20-day IV change is -0.1133 (-0.1090) for QEA events, but 0.0327 (0.0292) for MG events. The medians suggest that the 20-day IV decreased by about 10% for about half of the firms after they announced quarterly earnings, but increased by about 3% for about half of the firms after they released unbundled management guidance. The difference between QEA and MG events supports our argument in Section 2 that the announcer's 20-day IV before the pre-scheduled QEA date is elevated because of the heightened uncertainty about stock price movement on the announcement day. Since the unbundled MG dates are unknown to the public in advance, the change of the announcer's 20-day IV around unbundled MG events does not contain the same negative bias as the change of 20-day IV around QEA events.

[Table II is about here]

More importantly, the evidence in Panel A of Table II supports our first hypothesis that the expected value of the change of the announcers' forward IV is zero. We observe in Panel A that the average change of the announcer's forward IV is very close to zero for both QEA and MG events – the mean (median) change of the announcer's forward IV is only 0.0030 (-0.0018) for QEA events and 0.0061 (0.0009) for MG events. On the other hand, since the new information can have either positive or negative implications about the announcer's future volatility, there exists significant heterogeneity in the forward IV change after both QEA and MG events. For example, the 25th and 75th percentiles of the forward IV change after MG events are -0.020 and 0.025 respectively, which suggests that the announcer's forward IV decreases (increases) by more than 2% (2.5%) for about 25% of the MG events.

Panel B of Table II shows descriptive statistics about the IV changes for the suppliers of the announcers. For the sample of QEA events, in contrast to the large negative mean (median) of the change of the announcer's 20-day IV that we observe in Panel A, the change of the supplier's 20-day IV has a positive mean (median) of 0.0813 (0.0739). Similarly, the change of the supplier's 20-day IV after unbundled MG events has a positive mean (median) of 0.0548 (0.0481). The evidence supports that the sharp decline in the announcer's 20-day IV after QEA events is caused by the elevated pre-announcement uncertainty about the firm's own stock price movement on the announcement day.

Moreover, Panel B of Table II shows that the mean (median) of the supplier's forward IV change is very close to zero, being 0.0025 (-0.0006) after QEA events and 0.0041 (0.0008) after MG events. There is also significant heterogeneity in the suppliers' forward IV change, with the standard deviation being 0.0884 after QEA events and 0.0833 after MG events. The evidence again supports our first hypothesis that the distribution of the forward IV change centers at zero.

Overall, the results in Table II are consistent with our arguments in Section 2 and support our first hypothesis. The change of the forward IV after a disclosure event is not affected by the pre-announcement uncertainty about the announcement-day stock price movement, regardless of whether the event is pre-scheduled or unscheduled. Hence, the change of the forward IV is an unbiased measure of new volatility information in corporate disclosures and is a better instrument to test our second hypothesis on the VIT effect than the change of the 20-day IV.

4.2 Information Content in Forward IV

If the change of forward IV around the announcement date captures new information about future uncertainty, it must be positively related to the realized volatility in the post-announcement period. We examine the relationship between the change of forward IV and the realized volatility in a regression model with the realized volatility as the dependent variable and the change of forward IV as an independent variable. To compare information content in forward IV with that in 20-day IV, we include both the change of forward IV and the change of 20-day IV in the same regression model. The variable that has greater information content is expected to have a larger coefficient. Specifically, we estimate the following three regression models.

Model R1: *RV ~ FV_Pre*
Model R2: *RV ~ FV_Pre* + Δ*FV*
Model R3: *RV ~ FV_Pre* + Δ*FV* + *20dIV_Pre* + Δ*20dIV*

The dependent variable is the realized volatility of each firm in the period between the 21st and 182nd calendar day after the earning announcement day, which is calculated according to $RV = \sqrt{252 * \sum_{i=1}^{n} r_i^2}$, where r_i is the log return on day *i* and *n* is the number of days with non-missing log return. We require that there must be at least 100 days with non-missing log return. We delete observations with extreme value of *RV* beyond the 0.1% and 99.9% of the distribution. The independent variables *FV_Pre* and *20dIV_Pre* represent the level of forward IV and 20-day IV before the announcement day. The independent variables Δ*FV* and Δ*20dIV* measures the changes of forward IV and 20-day IV, respectively.

We use the sample of QEA events described in Table I and estimate the regressions for the sample of the announcing customers. The estimation results are presented in Table III with the t-statistic in parenthesis based on the standard error clustered at the firm level. We note two important findings. First, the pre-announcement level of forward IV is more strongly related to the realized volatility than the pre-announcement level of 20-day IV. In Equation (3) that includes both *FV_Pre* and *20dIV_Pre*, the coefficients of *FV_Pre* and *20dIV_Pre* are 0.3488 and 0.1793 respectively. The coefficients suggest that the impact of an increase in the pre-announcement forward IV on the future volatility is twice as large as the impact of an increase of the same magnitude in the pre-announcement 20-day IV.

[Table III is about here]

Second, the change of forward IV captures greater information content than the change of 20-day IV. In Equation (3) that includes both ΔFV and $\Delta 20dIV$, the coefficients of ΔFV and $\Delta 20dIV$ are 0.1540 and 0.0015 respectively. The coefficients suggest that an increase in forward IV is significantly and positively related to the realized volatility, while an increase in 20-day IV has no significant relationship with the realized volatility.

Overall, the results in Table III demonstrate that forward IV is informative about the firm's future volatility, which suggests using the change of forward IV around disclosure events to capture new volatility information.

5 Testing the VIT Effect

5.1 Regression Analysis

The evidence above shows that corporate disclosures, including mandatory quarterly earnings announcements and voluntary management guidance, have a significant impact on the expected future volatility of both the announcer and their suppliers. Prior studies demonstrate that there exist information complementarities between customers and suppliers, and information about a customer firm is useful in assessing business performance and prospects of its suppliers (e.g., Hertzel et al. 2008; Guan, Wong, and Zhang, 2015; Luo and Nagarajan, 2015; Barrot and Sauvagnat. 2016; Cen et al., 2018; Bushee, Kim-Gina, and Leung, 2020). In this section, we test our second hypothesis about the VIT effect from customers to their suppliers. Specifically, we test whether the change of the announcing customer's forward IV is positively related to the change of its supplier's forward IV, by estimating the following regression model.

Model 1: $\Delta SupFV \sim \Delta CusFV + \Delta VIX + \Delta VIX\_LargeSup + \Delta VIX\_SmallSup + CusRet + SupRet + SupBeta + LogSupMV + LogSupBM + \text{Fixed Effects}$

The dependent variable in Model 1 is the change of the supplier's forward IV ($\Delta SupFV$). The independent variables include the change of the announcing customer's forward IV ($\Delta CusFV$), the change of the CBOE VIX index (ΔVIX), the announcing customer's event-window return (*CusRet*), the supplier's event-window return (*SupRet*), the supplier's beta (*SupBeta*), the logarithm of the supplier's CPI-adjusted market capitalization (*LogSupMV*), and the logarithm of the supplier's book-to-market-equity ratio (*LogSupBM*). Since the suppliers' market value and book-to-market ratio are skewed to the right, we use the logarithm of market value *LogSupMV* and the logarithm of book-to-market ratio *LogSupBM* in the regression. In addition, we sort suppliers in each quarter into terciles by their market value at the end of the previous quarter and construct the two variables in the model, $\Delta VIX\_LargeSup$ and $\Delta VIX\_SmallSup$, to allow for a differential impact of the VIX change on large- and small-size suppliers. The definition of all variables is described in details in Appendix B. The model also includes fixed effects for customers and calendar years.

Our second hypothesis predicts that the customer forward IV change ($\Delta CusFV$) has a positive and significant coefficient in Model 1. The coefficient of ΔVIX is expected to be significantly positive, and the coefficient of $\Delta VIX\_LargeSup$ is expected to be significantly positive as VIX may have a greater impact on large firms. The leverage effect (Black 1976) suggests that the coefficient of *SupRet* is negative and significant. The sign of the coefficient of *CusRet* is undetermined because the new information captured by the customer's event-window return may be subsumed by the supplier's event-window return.

One may argue that, even though the evidence in Table II shows a downward bias in the change in the announcing customer's short-term implied volatility (i.e., $\Delta Cus20dIV$), it may contain some new information about the customer's future return volatility and omitting this variable may lead to a biased estimate of the coefficient of $\Delta CusFV$ in Model 1. To assess the effect of omitting this variable, we estimate the following Model 2 that includes $\Delta Cus20dIV$ as an additional independent variable.

Model 2: $\Delta SupFV \sim \Delta CusFV + \Delta Cus20dIV + \Delta VIX + \Delta VIX\_LargeSup + \Delta VIX\_SmallSup +$

$CusRet + SupRet + SupBeta + LogSupMV + LogSupBM +$ Fixed Effects

Table IV reports descriptive statistics of the control variables: ΔVIX, *CusRet*, *SupRet*, *SupBeta*, *LogSupMV*, and *LogSupBM*. The statistics in Panel A are for the sample of QEA events, and those in Panel B are for the sample of MG events. Despite the big difference between the number of QEA events (190,325) and that of MG events (64,116), the statistics of these variables show similar empirical distributions for both samples. One notable difference is that the distribution of the customer event-window return is more spread out in the sample of QEA events than in the sample of MG events.

[Table IV is about here]

Table V reports the Pearson correlation coefficients between these variables for the QEA events (the MG events) in the upper-right (lower-left) half of the table. We observe that, for both QEA and MG events, the announcing customer's IV changes, Δ*CusFV* and Δ*Cus20dIV*, are positively correlated with the supplier's IV changes, Δ*SupFV* and Δ*Sup20dIV*. Interestingly, the supplier 20-day IV change Δ*Sup20dIV* is negatively correlated with the supplier forward IV change Δ*SupFV*, whereas the customer 20-day IV change Δ*Cus20dIV* is positively correlated with the customer forward IV change Δ*CusFV*. The change of the VIX index Δ*VIX* is positively correlated with the IV changes of both customers and suppliers, but negatively correlated with their event-window returns. The suppliers' firm characteristics – *SupBeta*, *LogSupMV*, and *LogSupBM*, tend to have weak correlation with their IV changes. It is worthy to note that the correlation coefficient between Δ*Cus20dIV* and Δ*CusFV* is much smaller for the QEA events than that for the MG events. This is consistent with the observation in Table II and our argument in Section 2 that, because of the elevated pre-announcement uncertainty, there is a negative bias in Δ*Cus20dIV* for the QEA events but not for the MG events; in contrast, Δ*CusFV* is free of this bias for both the QEA and MG events. Since the bias introduces noise in Δ*Cus20dIV* for the QEA events, the correlation between Δ*Cus20dIV* and Δ*CusFV* for the QEA events is lower than that for the MG events.

[Table V is about here]

We estimate Models 1 and 2 for the QEA and MG samples separately and report the estimation results in Table VI. The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below the respective coefficient. The estimated coefficient of Δ*CusFV* in Model 1 is 0.0259 for the QEA sample and 0.0512 for the MG sample; both are highly significant. This means that the new information in the customer's disclosure has a significant impact on the expected volatility of the supplier's future stock return. In addition, the customer's management guidance has a greater impact on the supplier forward IV than its earnings announcement. As for the effects of the control variables, the change of the VIX index has a significantly positive coefficient, which is consistent with the prior studies that document the existence of a market-wide volatility factor. Moreover, the expected volatility of large-size suppliers is more closely related to the change of market volatility than small-size suppliers. The coefficient of the supplier event-window return (*SupRet*) is significantly negative, which is consistent with the leverage effect. While the coefficient of the customer event-window return (*CusRet*) is also negative and significant, its magnitude is only a small fraction of that of the supplier event-window return. This suggests that because of the return spillover effect, the supplier event-window return largely subsumes the effect of the customer event-window return.

[Table VI is about here]

The estimation results of Model 2 are similar to those of Model 1. Adding the independent variable Δ*Cus20dIV* in Model 2 does not lead to any notable change in the coefficients of the other variables in the model. The variable itself has a significantly positive coefficient for QEA events but an insignificant coefficient for MG events. The evidence suggests that for QEA events, Δ*Cus20dIV* contains some information about the supplier's future volatility that is not subsumed by Δ*CusFV*; whereas, for MG events, Δ*CusFV* alone captures all the information that is relevant to the suppliers' future volatility. Overall, the estimation results in Table VI support our second hypothesis that new information in the customer's public disclosures affects market expectation of its supplier's future volatility.

5.2 Cross-sectional Variation of the VIT Effect

The FactSet Revere Supply Chain database has a comprehensive coverage of supply-chain relationships, which enables us to measure a firm's supply-chain characteristics accurately. We construct three measures of the announcer's supply-chain characteristics for each event in our sample. First, the number of suppliers refers to the number of distinct suppliers that the announcer has at the end of the calendar quarter immediately before the event date. Second, the duration of each customer-supplier relationship is equal to the number of quarters the relationship has existed in the FactSet Revere database before the event date. Third, the customer sales percentage is equal to the proportion of sales to the announcer over the total annual sales of its supplier in the supplier's most recent fiscal year before the disclosure event. Table VII reports descriptive statistics of these supply-chain characteristics for the QEA and MG samples in Panel A and B, respectively.

[Table VII is about here]

The empirical distributions of these supply-chain characteristics are very similar for both QEA and MG samples. Although the number of suppliers has a larger median for the MG sample than for the QEA sample, its mean, standard deviation, and the other key percentiles are similar for both samples. The mean duration of the relationship between the announcer and its supplier is 12.3 and 12.0 quarters for the QEA and MG samples, respectively, while the median duration is eight quarters for both samples. The FactSet Revere database collects sales information from public disclosures, but not all suppliers disclose, to the public, information about their sales amount to a major customer. Thus, the customer sales percentage is available for only 17,560 QEA events (about 9.2% of the QEA sample) and 8,479 MG events (about

13.2% of the MG sample). The mean (median) customer sales percentage is 17.8% (14.0%) and 18.3% (14.8%) for the QEA and MG samples, respectively.

To formally test our third hypothesis about the influence of supply-chain characteristics on the VIT effect, we extend Model 2 to allow for the cross-sectional difference associated with each characteristic. First, we study the influence of firm size and the number of suppliers with Models 3 and 4.

Model 3: $\Delta SupFV \sim \Delta CusFV + \Delta CusFV\_LargeCus + \Delta CusFV\_SmallCus + DumLargeCus + DumSmallCus$ + controls + Fixed Effects

Model 4: $\Delta SupFV \sim \Delta CusFV + \Delta CusFV\_LargeNS + \Delta CusFV\_SmallNS + DumLargeNS + DumSmallNS$ + controls + Fixed Effects

In Model 3, the coefficient of the variable Δ*CusFV_LargeCus* (Δ*CusFV_SmallCus*) captures the incremental VIT effect from Δ*CusFV* to Δ*SupFV* when the announcing customer has a large (small) market value. We sort the announcing customers by their market value into terciles (small, medium, and large) at the end of each calendar quarter. The two dummy variables, *DumLargeCus* and *DumSmallCus*, are equal to one if the announcing customer is in the large and small terciles, respectively. The variable Δ*CusFV_LargeCus* (Δ*CusFV_SmallCus*) is the interaction term between Δ*CusFV* and *DumLargeCus* (*DumSmallCus*). In Model 4, the coefficient of Δ*CusFV_LargeNS* (Δ*CusFV_SmallNS*) captures the incremental VIT effect from Δ*CusFV* to Δ*SupFV* when the announcing customer has a large (small) number of suppliers. We sort the announcing customers by their number of suppliers into terciles (small, medium, and large) at the end of each calendar quarter. The two dummy variables, *DumLargeNS* and *DumSmallNS*, are equal to one if the announcing customer is in the large and small tercile, respectively. The variable Δ*CusFV_LargeNS* (Δ*CusFV_SmallNS*) is the interaction term between Δ*CusFV* and *DumLargeNS* (*DumSmallNS*). In addition, both models include the variable Δ*Cus20dIV*, the other control variables in Model 2, and the fixed effects for customers and years.

We estimate Models 3 and 4 for the QEA and MG samples, separately. Panel A of Table VIII reports the estimated coefficients of the key independent variables.[11] The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below the respective coefficient. We also report the difference between the coefficients of Δ*CusFV_LargeCus* and Δ*CusFV_SmallCus* in Model 3 and the difference between the coefficients of Δ*CusFV_LargeNS* and Δ*CusFV_SmallNS* in Model 4, together with the F-test statistic and its associated p-value for testing the significance of these differences.

The results show that firm size and the number of suppliers have a significant cross-sectional impact on the VIT effect. In Model 3, the difference between the coefficients of Δ*CusFV_LargeCus* and Δ*CusFV_SmallCus* is 0.0263 for the QEA sample and 0.1003 for the MG sample. In Model 4, the difference between the coefficients of Δ*CusFV_LargeNS* and Δ*CusFV_SmallNS* in Model 4 is 0.0330 for the QEA sample and 0.0764 for the MG sample. The differences in both models are statistically significant at 1% level. The evidence suggests that disclosures by customers of large firm size and customers with a large number of suppliers have a stronger impact on their suppliers' future volatility.

[Table VIII is about here]

Next, we use Models 5 and 6 to study the influence of the relationship duration and the customer sales percentage.

[11] The full estimation results are in Appendix C.

Model 5: $\Delta SupFV \sim \Delta CusFV + \Delta CusFV\_LongD + \Delta CusFV\_ShortD + \Delta DumLongD + \Delta DumShortD$ + controls + Fixed Effects

Model 6: $\Delta SupFV \sim \Delta CusFV + \Delta CusFV\_HighSales\% + \Delta CusFV\_LowSales\% + DumHighSales\% + DumLowSales\%$ + controls + Fixed Effects

In Model 5, the coefficient of the variable Δ*CusFV_LongD* (Δ*CusFV_ShortD*) captures the incremental VIT effect from Δ*CusFV* to Δ*SupFV* when the duration of the relationship between the announcing customer and its suppliers is longer than three years and undisrupted in the past three years (shorter than or equal to one quarter). In Model 6, the coefficient of the variable Δ*CusFV_HighSales%* (Δ*CusFV_LowSales%*) captures the incremental VIT effect from Δ*CusFV* to Δ*SupFV* when sales to the announcing customer is at least 15% (less than 15%) of the supplier's annual sales. Both models include the respective dummy variables, the variable Δ*Cus20dIV*, the other control variables in Model 2, and the fixed effects for customers and years.

Panel B of Table VIII reports the estimation results of the key independent variables in Models 5 and 6 for the QEA and MG sample, separately. In Model 5, the difference between the coefficients of Δ*CusFV_LongD* and Δ*CusFV_ShortD* is 0.0182 for the QEA sample and 0.0483 for the MG sample; both differences are highly significant. In Model 6, the difference between the coefficients of Δ*CusFV_HighSales%* and Δ*CusFV_LowSales%* is 0.0314 for the QEA sample and 0.0547 for the MG sample; the magnitude of these differences is relatively large, although they are not statistically significant at the conventional level. Overall, the evidence supports our third hypothesis that the VIT effect is stronger when the customers and suppliers have stronger economic links.

6 Conclusion

We use the change of option-implied forward volatility around a firm's corporate disclosure event to quantify new information about the firm's future volatility. We find that the distribution of the change of forward volatility centers around zero after quarterly earnings announcements (QEA) and unbundled management guidance (MG), which is a necessary condition for being an unbiased measure of new volatility information. In contrast, the change of option-implied short-term volatility drops sharply after the QEA events but increases moderately after the unbundled MG events. We show analytically that the negative bias in the change of short-term implied volatility after the QEA events is caused by the elevated announcement-day volatility prior to earnings announcements. The change of forward volatility is free of the bias.

We use our measure of new volatility information to investigate how new information about a customer's future volatility is transferred to its suppliers. Our empirical results show a significant volatility information transfer (VIT) effect, that is, the new volatility information released by a firm's earnings announcements or management guidance has a significant impact on market expectation of its supplier's future volatility. Moreover, consistent with the predictions of the production network theory of HKLV (2020), we find that the VIT effect is stronger if the announcer is larger in firm size, has a greater number of suppliers, and has a stronger economic link with its suppliers in terms of the customer sales percentage and the duration of customer-supplier relationship.

This study contributes to the literature by proposing an unbiased measure of new volatility information around corporate disclosure events and demonstrating the intricacy of the impact of corporate disclosures on market expectation of the announcers and their related firms' future stock return volatility. The empirical results are consistent with the production network explanation of firm-level volatility comovement.

Conflict of Interest

No conflict of interest to disclose.

Data Availability

The data underlying this article were provided by commercial database providers under license. The datasets were purchased through our research funding or our institutions. As such, we do not personally own the data and would not be allowed to make them available to third parties. Part of the data that were generated in the research process will be shared on request to the corresponding author with permission of the relevant third parties.

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Figure 1. Illustration of the Change of Expected Variances around an Announcement Day

An announcement occurs on day *t*. The pre-announcement 6-month expected variance on day *t-1* is denoted by $\sigma^2_{t-1,t+182}$, and the post-announcement 6-month expected variance on day *t* is denoted by $\sigma^2_{t,t+182}$. The pre-announcement 20-day expected variance on day *t-1* is denoted by $\sigma^2_{t-1,t+20}$, and the post-announcement 20-day expected variance on day *t* is denoted by $\sigma^2_{t,t+20}$. The pre-announcement forward variance on day *t-1* is denoted by $FV_{t-1,t+20,t+182}$, and the post-announcement forward variance on day *t* is denoted by $FV_{t,t+20,t+182}$. Mathematical derivation in Appendix A shows that the change from day *t-1* to day *t* of the 6-month expected variance can be approximated by the weighted average of the change of the 20-day expected variance and the change of the forward variance, as in the following equation.

$$\sigma^2_{t,t+182} - \sigma^2_{t-1,t+182} \approx \left(\frac{20}{182}\right)\left[\sigma^2_{t,t+20} - \sigma^2_{t-1,t+20}\right] + \left(\frac{162}{182}\right)\left[FV_{t,t+20,t+182} - FV_{t-1,t+20,t+182}\right]$$

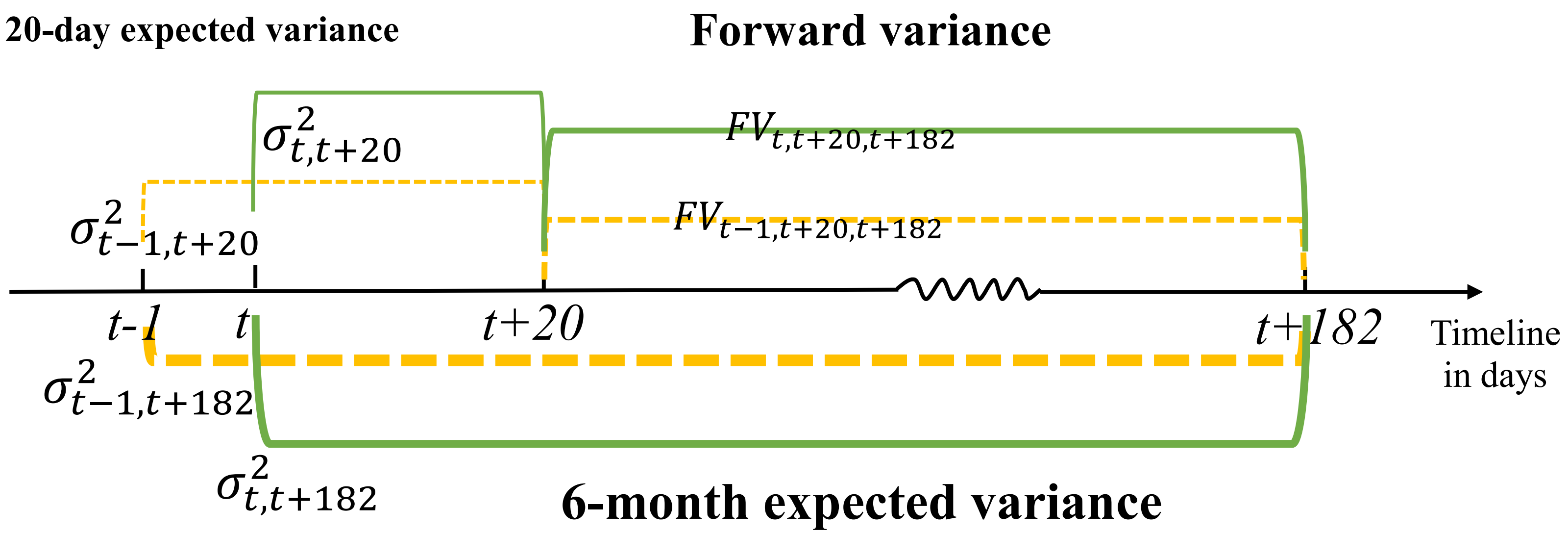

Table I. Sample Selection

The table presents the key steps that we follow to select the sample of events. We merge the FactSet Revere Supply Chain database, the CRSP/Compustat Merged database, the OptionMetrics database, and the Thomson Reuters IBES Guidance database. We identify the customer-supplier pairs in the FactSet Revere database. In Panel A, for the sample of quarterly earnings announcement (QEA) events, we use the QEA dates in the Compustat database. For each customer that released a QEA, there may be more than one supplier. A QEA event refers to a unique pair of the announcing customer's QEA date and one of its suppliers. In Panel B, for the sample of management guidance (MG) events, we use the MG dates in the IBES Guidance database. A MG event refers to a unique pair of the announcing customer MG date and one of its suppliers.

Panel A: The Sample of QEA Events

Sample selection procedure	Number of QEA events
The initial sample of QEA events	475,614
after removal of overlapping events with the suppliers' own earnings announcements	298,957
after removal of customers in banking, financial institutions, and utilities industry	263,915
after removal of suppliers in banking, financial institutions, and utilities industry	252,284
after removal of observations with customer price or supplier price below $5	223,103
after removal of observations with extreme values at each end in the distribution of continuous variables that are used in the regression analysis	190,325

Panel B: The Sample of MG Events

Sample selection procedure	Number of MG events
The initial sample of MG events	381,199
after removal of overlapping events with the suppliers' own earnings announcements	268,373
after removal of overlapping events with the customers' own earnings announcements	88,563
after removal of customers in banking, financial institutions, and utilities industries	78,979
after removal of suppliers in banking, financial institutions, and utilities industries	76,383
after removal of observations with the customer price or supplier price below $5	70,352
after removal of observations with extreme values at each end in the distribution of continuous variables that are used in the regression analysis	64,116

Table II. Statistics about the Change of Implied Volatilities around Disclosure Events

For each customer disclosure date (day 0), we choose the pre-event window to include day -2 and day -1, and the post-event window to include day 1 and day 2. We calculate the pre-event (post-event) implied volatility (IV) as the square root of the average daily model-free implied variances in the pre-event (post-event) window. For each event and for both the announcing customer and its supplier, we calculate the change of the 20-day (forward) IV as the logarithm of the post-event 20-day (forward) IV minus the logarithm of the pre-event 20-day (forward) IV. Panel A of the table reports descriptive statistics about the change of the customer's 20-day IV (Δ*Cus20dIV*) and the change of the customer's forward IV (Δ*CusFV*). Panel B reports descriptive statistics about the change of the supplier's 20-day IV (Δ*Sup20dIV*) and the change of the supplier's forward IV (Δ*SupFV*).

Panel A: Statistics about the Change of the Customer's IV

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**
QEA events							
Δ*Cus20dIV*	-0.1133	-0.1090	0.1760	-0.407	-0.215	-0.006	0.159
Δ*CusFV*	0.0030	-0.0018	0.0857	-0.100	-0.031	0.031	0.125
MG events							
Δ*Cus20dIV*	0.0327	0.0292	0.1191	-0.144	-0.027	0.092	0.214
Δ*CusFV*	0.0061	0.0009	0.0606	-0.061	-0.020	0.025	0.097

Panel B: Statistics about the Change of the Supplier's IV

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**
QEA events							
Δ*Sup20dIV*	0.0813	0.0739	0.1403	-0.121	0.007	0.153	0.305
Δ*SupFV*	0.0025	-0.0006	0.0884	-0.106	-0.023	0.024	0.122
MG events							
Δ*Sup20dIV*	0.0548	0.0481	0.1285	-0.131	-0.010	0.118	0.255
Δ*SupFV*	0.0041	0.0008	0.0833	-0.093	-0.020	0.024	0.118

Table III. Information Content in Forward IV

We use the sample of QEA events described in Table I and estimate the following three regressions for the sample of customers.

Model R1: *RV ~ FV_Pre*
Model R2: *RV ~ FV_Pre + ΔFV*
Model R3: *RV ~ FV_Pre + ΔFV + 20dIV_Pre + Δ20dIV*

The dependent variable *RV* is the realized volatility of each customer in the period between the 21st and 182nd calendar day after the earning announcement day, which is calculated according to the formular $RV = \sqrt{252 * \sum_{i=1}^{n} r_i^2}$, where r_i is the log return on day *i* and *n* is the number of days with non-missing log return. We require that there must be at least 100 days with non-missing log return. We delete observations with extreme value of *RV* beyond the 0.1% and 99.9% of the distribution. The independent variables *FV_Pre* and *20dIV_Pre* represent the level of forward IV and 20-day IV before the announcement day. The independent variables Δ*FV* and Δ*20dIV* measure the changes of forward IV and 20-day IV, respectively. The table below presents the estimation results. The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below the respective coefficient.

	Model R1	**R2**	**R3**
Intercept	0.1548	0.1521	0.1285
	(37.87)	(37.13)	(34.99)
FV_Pre	0.5297	0.5423	0.3488
	(55.75)	(57.60)	(27.91)
Δ*FV*		0.2418	0.1540
		(22.32)	(13.93)
20dIV_Pre			0.1793
			(21.07)
Δ*20dIV*			0.0015
			(0.27)
R-squared	30.3%	31.5%	33.3%
#obs	46,028	46,028	46,028

Table IV. Statistics about the Control Variables

The table reports descriptive statistics of control variables in the regression models, including the change of the CBOE VIX index (ΔVIX), the customer's event-window return (*CusRet*), the supplier's event-window return (*SupRet*), the supplier's beta (*SupBeta*), the logarithm of the supplier's CPI-adjusted market capitalization (*LogSupMV*), and the logarithm of the supplier's book-equity-to-market-equity ratio (*LogSupBM*). All variables are defined in Appendix B. Panel A and B are for the samples of QEA and MG events, respectively.

Panel A: For the Sample of QEA Events

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**
ΔVIX	-0.0004	-0.0079	0.1072	-0.154	-0.063	0.051	0.189
CusRet	0.0038	0.0028	0.0861	-0.136	-0.039	0.049	0.141
SupRet	0.0013	0.0019	0.0504	-0.079	-0.023	0.027	0.079
SupBeta	1.2672	1.1840	0.5354	0.546	0.908	1.537	2.281
LogSupMV	7.4285	7.0531	2.0541	4.639	5.875	8.686	11.288
LogSupBM	-1.1356	-1.0463	0.8465	-2.690	-1.578	-0.578	0.057

Panel B: For the Sample of MG Events

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**
ΔVIX	-0.0023	-0.0076	0.0987	-0.151	-0.063	0.053	0.165
CusRet	-0.0019	0.0022	0.0615	-0.103	-0.027	0.027	0.083
SupRet	0.0014	0.0017	0.0536	-0.083	-0.025	0.028	0.084
SupBeta	1.2969	1.2116	0.5450	0.563	0.923	1.576	2.336
LogSupMV	7.1008	6.7931	1.8319	4.665	5.760	8.099	10.874
LogSupBM	-1.0798	-1.0077	0.7861	-2.518	-1.478	-0.570	0.037

Table V. Correlation Coefficients

The table reports the Pearson correlation coefficients between the key continuous variables. All variables are defined in Appendix B. The numbers in the upper-right (lower-left) half are for the sample of QEA (MG) events.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ*Sup20dIV*	(1)		-0.028	0.100	0.058	0.236	-0.060	-0.133	-0.022	0.055	-0.014
Δ*SupFV*	(2)	-0.024		0.042	0.056	0.155	-0.051	-0.108	-0.002	-0.001	0.007
Δ*Cus20dIV*	(3)	0.157	0.056		0.011	0.209	-0.150	-0.105	0.045	0.020	0.037
Δ*CusFV*	(4)	0.072	0.086	0.093		0.177	-0.144	-0.110	-0.010	0.025	-0.013
Δ*VIX*	(5)	0.199	0.156	0.287	0.283		-0.201	-0.358	0.016	-0.009	-0.004
Δ*CusRet*	(6)	-0.061	-0.070	-0.211	-0.244	-0.232		0.222	-0.008	0.007	-0.001
Δ*SupRet*	(7)	-0.111	-0.111	-0.127	-0.141	-0.309	0.292		-0.014	0.015	-0.004
SupBeta	(8)	-0.008	-0.010	0.009	0.005	-0.004	-0.013	-0.012		-0.240	0.011
LogSupMV	(9)	0.037	-0.027	0.005	0.010	-0.004	0.006	0.010	-0.250		-0.316
LogSupBM	(10)	-0.016	0.011	0.003	-0.006	0.005	-0.013	-0.010	-0.025	-0.300	

Table VI. Testing the VIT Effect from Customers to Suppliers

The table shows the estimation results of Models 1 and 2 for testing whether the change of the announcer's forward IV has a positive effect on the change of its supplier's forward IV.

Model 1: $\Delta SupFV \sim \Delta CusFV + \Delta VIX + \Delta VIX\_LargeSup + \Delta VIX\_SmallSup$
$+ CusRet + SupRet + SupBeta + LogSupMV + LogSupBM +$ Fixed Effects
Model 2: $\Delta SupFV \sim \Delta CusFV + \Delta Cus20dIV + \Delta VIX + \Delta VIX\_LargeSup + \Delta VIX\_SmallSup$
$+ CusRet + SupRet + SupBeta + LogSupMV + LogSupBM +$ Fixed Effects

The dependent variable in both Model 1 and 2 is the change of the supplier's forward IV ($\Delta SupFV$). The independent variables in both models are the same except that Model 2 includes an additional variable $\Delta Cus20dIV$. All variables are defined in Appendix B. The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below the respective coefficient.

Dependent variable	**Model 1: $\Delta SupFV$**		**Model 2: $\Delta SupFV$**	
	QEA events	**MG events**	**QEA events**	**MG events**
$\Delta CusFV$	0.0259	0.0512	0.0267	0.0514
	(7.43)	(5.51)	(7.65)	(5.54)
$\Delta Cus20dIV$			0.0085	0.0046
			(5.12)	(1.11)
ΔVIX	0.0854	0.0407	0.0828	0.0399
	(20.74)	(11.41)	(19.59)	(11.14)
$\Delta VIX\_LargeSup$	0.0874	0.0399	0.0877	0.0400
	(19.53)	(9.66)	(19.57)	(9.68)
$\Delta VIX\_SmallSup$	-0.0329	-0.0102	-0.0331	-0.0102
	(-5.38)	(-2.14)	(-5.41)	(-2.14)
CusRet	-0.0076	-0.0181	-0.0057	-0.0167
	(-2.85)	(-2.47)	(-2.12)	(-2.21)
SupRet	-0.1028	-0.1002	-0.1024	-0.1002
	(-20.50)	(-10.47)	(-20.45)	(-10.49)
SupBeta	-0.0001	-0.0027	-0.0001	-0.0027
	(-0.28)	(-3.51)	(-0.26)	(-3.50)
LogSupMV	-0.0002	-0.0013	-0.0002	-0.0013
	(-1.50)	(-5.07)	(-1.54)	(-5.07)
LogSupBM	0.0011	0.0005	0.0010	0.0005
	(3.66)	(0.92)	(3.63)	(0.92)
Fixed effects				
Customer	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R-squared	4.8%	6.0%	4.8%	6.0%
#obs	190,325	64,116	190,325	64,116

Table VII. Statistics about the Announcing Customers' Supply-chain Characteristics

The table reports descriptive statistics about three supply-chain characteristics of the announcing customers: the number of its suppliers, the customer Sales%, and the relationship duration. For each event, the number of suppliers is equal to the number of *distinct* suppliers that the announcing customer has in the FactSet Revere database at the end of the calendar quarter immediately before the announcement. The customer Sales% is the proportion of a supplier's sales to its customer out of the total annual sales of the supplier in its most recent fiscal year before the event. The customer Sales% is missing for many observations in the FactSet Revere database. The relationship duration is equal to the number of quarters the customer-supplier relationship has existed in the FactSet Revere database before the event date. Panel A and B are for the samples of QEA and MG events, respectively.

Panel A: For the sample of QEA events

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**	**#events**
Number of suppliers	54.2	27	69.7	3	9	75	193	190325
Relationship duration	12.3	8	12.4	1	3	17	39	190325
Customer Sales%	17.8	14	13.4	4.7	10.4	21	39.3	17560

Panel B: For the sample of MG events

	Mean	**Median**	**StdDev**	**P5**	**Q1**	**Q3**	**P95**	**#events**
Number of suppliers	57.5	40	64.5	3	12	80	203	64116
Relationship duration	12.0	8	11.6	1	3	17	37	64116
Customer Sales%	18.3	14.8	14.2	5	11	21	41	8479

Table VIII. Cross-sectional Variation in the VIT Effect

We estimate the following models for the samples of QEA events and MG events, separately. All of the models include the control variables – Δ*Cus20dIV*, Δ*VIX*, Δ*VIX_LargeSup*, Δ*VIX_SmallSup*, *CusRet*, *SupRet*, *SupBeta*, *LogSupMV*, and *LogSupBM*, and the fixed effects for customers and years. All variables are defined in Appendix B. The table reports the estimated coefficients that are relevant for testing the VIT effect. The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below each coefficient. The full estimation results are reported in Appendix C.

Model 3: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LargeCus* + Δ*CusFV_SmallCus* + *DumLargeCus* + *DumSmallCus* + controls + Fixed Effects

Model 4: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LargeNS* + Δ*CusFV_SmallNS* + *DumLargeNS* + *DumSmallNS* + controls + Fixed Effects

Model 5: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LongD* + Δ*CusFV_ShortD* + *DumLongD* + *DumShortD* + controls + Fixed Effects

Model 6: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_HighSales%* + Δ*CusFV_LowSales%* + *DumHighSales%* + *DumLowSales%* + controls + Fixed Effects

Panel A: Effects of the Announcing Customer's Firm Size and the Number of Suppliers

	Model 3			Model 4	
	QEA	**MG**		**QEA**	**MG**
Δ*CusFV*	0.0322	0.0773	Δ*CusFV*	0.0209	0.0578
	(3.49)	(3.77)		(4.06)	(3.22)
Δ*CusFV_LargeCus* (γ_1)	0.0148	0.0423	Δ*CusFV_LargeNS* (γ_1)	0.0344	0.0486
	(1.05)	(1.29)		(2.44)	(1.35)
Δ*CusFV_SmallCus* (γ_2)	-0.0115	-0.0580	Δ*CusFV_SmallNS* (γ_2)	0.0014	-0.0278
	(-1.17)	(-2.61)		(0.22)	(-1.35)
Significance test of coefficient difference			*Significance test of coefficient difference*		
Difference ($\gamma_1 - \gamma_2$)	0.0263	0.1003	Difference ($\gamma_1 - \gamma_2$)	0.0330	0.0764
F-statistic	12.37	42.36	F-statistic	22.11	23.57
p-value	<0.001	<0.001	p-value	<0.001	<0.001

Panel B: Effects of the Customer-supplier Relationship Duration and Customer Sales%

	Model 5			Model 6	
	QEA	**MG**		**QEA**	**MG**
Δ*CusFV*	0.0238	0.0602	Δ*CusFV*	0.0266	0.0516
	(4.63)	(4.77)		(7.58)	(5.86)
Δ*CusFV_LongD* (γ_1)	0.0143	0.0131	Δ*CusFV_HighSales%* (γ_1)	0.0276	0.0226
	(2.04)	(0.77)		(1.01)	(0.57)
Δ*CusFV_ShortD* (γ_2)	-0.0039	-0.0352	Δ*CusFV_LowSales%* (γ_2)	-0.0038	-0.0221
	(-0.60)	(-2.33)		(-0.21)	(-0.58)
Significance test of coefficient difference			*Significance test of coefficient difference*		
Difference ($\gamma_1 - \gamma_2$)	0.0182	0.0483	Difference ($\gamma_1 - \gamma_2$)	0.0314	0.0547
F-statistic	9.79	12.30	F-statistic	1.44	1.36
p-value	0.002	<0.001	p-value	0.230	0.244

Appendix A

Mathematical Derivation

We derive Equation (3) in Section 2.1 as follows. Let $\sigma_{t,T}^2$ be the expected variance of the stock return between day *t+1* and day *T* inclusively, conditional on the information on day *t*. It can be expressed mathematically in the discrete-time form as

$$\sigma_{t,T}^2 = \frac{1}{T-t}\sum_{u=t+1}^{T} \sigma_{u|t}^2 \qquad (A1)$$

where $\sigma_{u|t}^2$ is the expected variance on day *u* conditional on the available information on day *t*.

From Equation (*A*1), we can derive the change of the expected variance from day *t-1* to day *t* as follows,

$$\sigma_{t,T}^2 - \sigma_{t-1,T}^2 = \left(\frac{1}{T-t}\right)\sum_{u=t+1}^{T} \sigma_{u|t}^2 - \left(\frac{1}{T-t+1}\right)\sum_{u=t}^{T} \sigma_{u|t-1}^2$$

$$= \left(\frac{1}{T-t}\right)\left[\sum_{u=t+1}^{T} \sigma_{u|t}^2 + \left(\frac{T-t}{T-t+1}\right)\sum_{u=t+1}^{T} \sigma_{u|t-1}^2\right]$$

$$= \left(\frac{1}{T-t}\right)\left[\sum_{u=t+1}^{T} \left(\sigma_{u|t}^2 - \sigma_{u|t-1}^2\right) + \sum_{u=t+1}^{T} \sigma_{u|t-1}^2 + \left(\frac{T-t}{T-t+1}\right)\sum_{u=t+1}^{T} \sigma_{u|t-1}^2\right]$$

$$= \left(\frac{1}{T-t}\right)\left[\sum_{u=t+1}^{T} \left(\sigma_{u|t}^2 - \sigma_{u|t-1}^2\right) + (T-t+1)\sigma_{t-1,T}^2 - \sigma_{t|t-1}^2 - (T-t)\sigma_{t-1,T}^2\right]$$

$$= \left(\frac{1}{T-t}\right)\left[\sum_{u=t+1}^{T} \left(\sigma_{u|t}^2 - \sigma_{u|t-1}^2\right) + \left(\sigma_{t-1,T}^2 - \sigma_{t|t-1}^2\right)\right] \qquad (A2)$$

Suppose that an announcement occurs on day *t*. The pre-announcement long-term expected variance on day *t-1* is denoted by σ_{t-1,T_2}^2, and the post-announcement long-term expected variance on day *t* is denoted by σ_{t,T_2}^2. The pre-announcement short-term expected variance on day *t-1* is denoted by σ_{t-1,T_1}^2, and the post-announcement short-term expected variance on day *t* is denoted by σ_{t,T_1}^2. The pre-announcement expected forward variance on day *t-1* is denoted by FV_{t-1,T_1,T_2}, and the post-announcement 6-month expected variance on day *t* is denoted by FV_{t,T_1,T_2}. These expected variances can be written in mathematical terms as

$\sigma_{t-1,T_2}^2 = \frac{1}{T_2-t+1}\sum_{u=t}^{T_2} \sigma_{u|t}^2$, $\sigma_{t-1,T_1}^2 = \frac{1}{T_1-t+1}\sum_{u=t}^{T_1} \sigma_{u|t}^2$, $FV_{t-1,T_1,T_2} = \frac{1}{T_2-T_1}\sum_{u=T_1+1}^{T_2} \sigma_{u|t-1}^2$,

$\sigma^2_{t,T_2} = \frac{1}{T_2-t}\sum_{u=t+1}^{T_2}\sigma^2_{u|t}$, $\sigma^2_{t,T_1} = \frac{1}{T_1-t}\sum_{u=t+1}^{T_1}\sigma^2_{u|t}$, $FV_{t,T_1,T_2} = \frac{1}{T_2-T_1}\sum_{u=T_1+1}^{T_2}\sigma^2_{u|t}$.

We now derive the mathematical expression of the change from day *t-1* to day *t* of the long-term expected variance (i.e., Equation (3) in the paper) as follows. Note that the above Equation (A2) is used twice in the following proof.

$$\sigma^2_{t,T_2} - \sigma^2_{t-1,T_2} = \left(\frac{1}{T_2-t}\right)\left[\sum_{u=t+1}^{T_2}\left(\sigma^2_{u|t} - \sigma^2_{u|t-1}\right) + \left(\sigma^2_{t-1,T_2} - \sigma^2_{t|t-1}\right)\right]$$

$$= \left(\frac{1}{T_2-t}\right)\left[\sum_{u=t+1}^{T_1}\left(\sigma^2_{u|t} - \sigma^2_{u|t-1}\right) + \sum_{u=T_1+1}^{T_2}\left(\sigma^2_{u|t} - \sigma^2_{u|t-1}\right)\right.$$
$$\left. + \left(\sigma^2_{t-1,T_2} - \sigma^2_{t|t-1}\right)\right]$$

$$= \left(\frac{1}{T_2-t}\right)\left[\left(\sigma^2_{t-1,T_2} - \sigma^2_{t|t-1}\right) + \sum_{u=t+1}^{T_1}\left(\sigma^2_{u|t} - \sigma^2_{u|t-1}\right)\right]$$
$$+ \left(\frac{T_2-T_1}{T_2-t}\right)\left(FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}\right)$$

$$= \left(\frac{1}{T_2-t}\right)\left[\left(\sigma^2_{t-1,T_1} - \sigma^2_{t|t-1}\right) + \sum_{u=t+1}^{T_1}\left(\sigma^2_{u|t} - \sigma^2_{u|t-1}\right)\right]$$
$$+ \left(\frac{1}{T_2-t}\right)\left(\sigma^2_{t-1,T_2} - \sigma^2_{t-1,T_1}\right) + \left(\frac{T_2-T_1}{T_2-t}\right)\left(FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}\right)$$

$$= \left(\frac{T_1-t}{T_2-t}\right)\left(\sigma^2_{t,T_1} - \sigma^2_{t-1,T_1}\right) + \left(\frac{T_2-T_1}{T_2-t}\right)\left(FV_{t,T_1,T_2} - FV_{t-1,T_1,T_2}\right)$$
$$+ \left(\frac{1}{T_2-t}\right)\left(\sigma^2_{t-1,T_2} - \sigma^2_{t-1,T_1}\right) \qquad (A3)$$

Appendix B

Variable Definition

The following variables are used in the regression models in this study. For each customer announcement date (day 0), we choose the pre-event window to include day -2 and day -1, and the post-event window to include day 1 and day 2. We calculate the pre-event (post-event) implied volatility (IV) as the square root of the average model-free implied variance over the days in the pre-event (post-event) window.

Dependent Variables	
Δ*Sup20dIV*	Change of the supplier's 20-day IV For each event, Δ*Sup20dIV* is equal to the logarithm of the supplier's post-event 20-day IV minus the logarithm of the supplier's pre-event 20-day IV.
Δ*SupFV*	Change of the supplier's forward IV For each event, Δ*SupFV* is equal to the logarithm of the supplier's post-event forward IV minus the logarithm of the supplier's pre-event forward IV.
Key Independent Variables	
Δ*Cus20dIV*	Change of the announcing customer's 20-day IV For each event, Δ*Cus20dIV* is equal to the logarithm of the announcing customer's post-event 20-day IV minus the logarithm of the announcing customer's pre-event 20-day IV.
Δ*CusFV*	Change of the announcing customer's forward IV For each event, Δ*CusFV* is equal to the logarithm of the announcing customer's post-event forward IV minus the logarithm of the announcing customer's pre-event forward IV.
Control Variables	
Δ*VIX*	Change of the VIX index For each event, Δ*VIX* is equal to the logarithm of the average daily VIX index in the post-event window minus the logarithm of the average daily VIX index in the pre-event window.
Δ*VIX_LargeSup*	VIX change for large suppliers In each calendar quarter between June 2003 and December 2020, we group events into terciles (i.e., large, medium, small) according to the supplier's market value at the end of the previous calendar quarter. For each event, Δ*VIX_LargeSup* is equal to Δ*VIX* if the supplier is in the large supplier market value tercile, and equal to zero otherwise.
Δ*VIX_SmallSup*	VIX change for small suppliers In each calendar quarter between June 2003 and December 2020, we group events into terciles (i.e., large, medium, small) according to the supplier's market value at the end of the previous calendar quarter. For each event, Δ*VIX_SmallSup* is equal to Δ*VIX* if the supplier is in the small supplier market value tercile, and equal to zero otherwise.
CusRet	The announcing customer's event-window return For each event, *CusRet* is equal to the cumulative stock return in the five-trading-day window [-2, 2] by compounding the five daily returns of the announcing customer.
SupRet	The supplier's event-window return For each event, *SupRet* is equal to the cumulative stock return in the five-trading-day window [-2, 2] by compounding the five daily returns of the supplier.
SupBeta	The supplier's beta For each event, *SupBeta* is estimated with the supplier's daily returns in the one-year period that ends with the announcing customer's fiscal quarter before its announcement.

LogSupMV	Log (Supplier's market value) For each event, *LogSupMV* is equal to the logarithm of the supplier's market value ($ million) on the 10th trading day before the announcement. We calculate market value as the product of stock price and the number of shares outstanding in the CRSP database. We follow prior studies to adjust market value by the CPI index.
LogSupBM	Log (Supplier's book-to-market-equity ratio) For each event, *LogSupBM* is equal to the supplier's book value of equity in the most recent fiscal year before the announcement divided by the supplier's market value as defined above. We remove the observations that have a negative book value of equity.
Variables for Testing the Cross-sectional Variation of the VIT Effect	
Δ*CusFV_LargeCus* *DumLargeCus* Δ*CusFV_SmallCus* *DumSmallCus*	In each calendar quarter between June 2003 and December 2020, we rank the announcing customers by their market values at the end of the previous quarter and group events into terciles according to whether the announcing customers have a large, medium, or small firm size. For each event, *DumLargeCus* is equal to one and Δ*CusFV_LargeCus* is equal to Δ*CusFV* if the customer is in the large size tercile, and zero otherwise; *DumSmallCus* is equal to one and Δ*CusFV_SmallCus* is equal to Δ*CusFV* if the customer is in the small size tercile, and zero otherwise.
Δ*CusFV_LargeNS* *DumLargeNS* Δ*CusFV_SmallNS* *DumSmallNS*	In each calendar quarter between June 2003 and December 2020, we rank the announcing customers by the number of distinct suppliers that each of them has in the FactSet Revere database at the end of the previous calendar quarter and group events into terciles according to whether the announcing customers have a large, medium, or small number of suppliers (NS). For each event, *DumLargeNS* is equal to one and Δ*CusFV_LargeNS* is equal to Δ*CusFV* if the customer is in the large *NS* tercile, and zero otherwise; *DumSmallNS* is equal to one and Δ*CusFV_SmallNS* is equal to Δ*CusFV* if the customer is in the small *NS* tercile, and zero otherwise.
Δ*CusFV_HighSales%* *DumHighSales%* Δ*CusFV_LowSales%* *DumLowSales%*	For each event, *DumHighSales%* is equal to one and Δ*CusFV_HighSales%* is equal to Δ*CusFV* if sales to the announcing customer accounts for greater than 15% of the supplier's annual sales in its most recent fiscal year before the event, and zero otherwise; *DumLowSales%* is equal to one and Δ*CusFV_LowSales%* is equal to Δ*CusFV* if the customer sales percentage is positive but less than 15%, and zero otherwise.
Δ*CusFV_LongD* *DumLongD* Δ*CusFV_ShortD* *DumShortD*	For each event, the duration of the relationship between the announcing customer and its supplier is equal to the number of quarters the relationship had existed prior to the event. For each event, *DumLongD* is equal to one and Δ*CusFV_LongD* is equal to Δ*CusFV* if the duration of the relationship between the announcing customer and its supplier is greater than three years and undisrupted in the past three years, and zero otherwise; *DumShortD* is equal to one and Δ*CusFV_ShortD* is equal to Δ*CusFV* if the relationship duration is not greater than one quarter, and zero otherwise.

Appendix C

Full Estimation Results of the Regression Models

Table C1. Full Estimation Results for the Samples of QEA and MG Events

The table reports the full estimation results of the following regression models that are described in Section 4. We estimate each model for the samples of QEA and MG events, separately. The samples of QEA and MG events were obtained by following the steps in Panels A and B of Table I, respectively. All models include the same set of control variables: Δ*Cus20dIV*, Δ*VIX*, Δ*VIX_LargeSup*, Δ*VIX_SmallSup*, *CusRet*, *SupRet*, *SupBeta*, *LnSupMV*, *LnSupBM*, and the fixed effects for customers and years. All variables are defined in Appendix B. The t-statistic with clustered error adjustment (clustering at customers) is reported in parenthesis below the respective coefficient.

Model 3: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LargeCus* + Δ*CusFV_SmallCus* + *DumLargeCus* + *DumSmallCus* + controls + Fixed Effects

Model 4: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LargeNS* + Δ*CusFV_SmallNS* + *DumLargeNS* + *DumSmallNS* + controls + Fixed Effects

Model 5: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_LongD* + Δ*CusFV_ShortD* + *DumLongD* + *DumShortD* + controls + Fixed Effects

Model 6: Δ*SupFV* ~ Δ*CusFV* + Δ*CusFV_HighSales%* + Δ*CusFV_LowSales%* + *DumHighSales%* + *DumLowSales%* + controls + Fixed Effects

Table C1. Continued

	Model 3			Model 4	
	QEA events	**MG events**		**QEA events**	**MG events**
Δ*CusFV*	0.0322	0.0773	Δ*CusFV*	0.0209	0.0578
	(3.49)	(3.77)		(4.06)	(3.22)
Δ*CusFV_LargeCus*	0.0148	0.0423	Δ*CusFV_LargeNS*	0.0344	0.0486
	(1.05)	(1.29)		(2.44)	(1.35)
Δ*CusFV_SmallCus*	-0.0115	-0.0580	Δ*CusFV_SmallNS*	0.0014	-0.0278
	(-1.17)	(-2.61)		(0.22)	(-1.35)
DumLargeCus	-0.0012	-0.0013	*DumLargeNS*	0.0029	-0.0007
	(-0.75)	(-0.85)		(2.00)	(-0.43)
DumSmallCus	0.0019	0.0014	*DumSmallNS*	0.0002	0.0052
	(1.61)	(0.84)		(0.17)	(3.12)
Δ*Cus20dIV*	0.0084	0.0027	Δ*Cus20dIV*	0.0086	0.0039
	(5.15)	(0.66)		(5.23)	(0.98)
Δ*VIX*	0.0812	0.0373	Δ*VIX*	0.0813	0.0381
	(18.72)	(10.37)		(19.25)	(10.39)
Δ*VIX_LargeSup*	0.0885	0.0412	Δ*VIX_LargeSup*	0.0886	0.0405
	(19.89)	(9.89)		(20.14)	(9.66)
Δ*VIX_SmallSup*	-0.0333	-0.0102	Δ*VIX_SmallSup*	-0.0332	-0.0102
	(-5.45)	(-2.15)		(-5.41)	(-2.14)
CusRet	-0.0052	-0.0132	*CusRet*	-0.0050	-0.0152
	(-1.89)	(-1.71)		(-1.86)	(-1.96)
SupRet	-0.1018	-0.0992	*SupRet*	-0.1018	-0.0996
	(-20.34)	(-10.45)		(-20.37)	(-10.38)
SupBeta	-0.0001	-0.0027	*SupBeta*	-0.0002	-0.0027
	(-0.25)	(-3.50)		(-0.31)	(-3.48)
LogSupMV	-0.0002	-0.0013	*LogSupMV*	-0.0002	-0.0013
	(-1.56)	(-5.04)		(-1.58)	(-5.00)
LogSupBM	0.0010	0.0005	*LogSupBM*	0.0010	0.0005
	(3.59)	(0.94)		(3.62)	(0.94)
Fixed effects			Fixed effects		
Customer	Yes	Yes	Customer	Yes	Yes
Year	Yes	Yes	Year	Yes	Yes
R-squared	4.8%	6.1%	R-squared	4.9%	6.1%
#obs	190,325	64,116	#obs	190,325	64,116

Table C1. Continued

	Model 5			Model 6	
	QEA events	**MG events**		**QEA events**	**MG events**
Δ*CusFV*	0.0238	0.0602	Δ*CusFV*	0.0266	0.0516
	(4.63)	(4.77)		(7.58)	(5.86)
Δ*CusFV_LongD*	0.0143	0.0131	Δ*CusFV_HighSales%*	0.0276	0.0226
	(2.04)	(0.77)		(1.01)	(0.57)
Δ*CusFV_ShortD*	-0.0039	-0.0352	Δ*CusFV_LowSales%*	-0.0038	-0.0221
	(-0.60)	(-2.33)		(-0.21)	(-0.58)
DumLongD	-0.0006	0.0010	*DumHighSales%*	0.0006	0.0014
	(-1.04)	(1.16)		(0.41)	(1.16)
DumShortD	-0.0011	-0.0002	*DumLowSales%*	0.0016	-0.0004
	(-2.04)	(-0.19)		(1.61)	(-0.30)
Δ*Cus20dIV*	0.0085	0.0048	Δ*Cus20dIV*	0.0085	0.0046
	(5.15)	(1.17)		(5.12)	(1.11)
Δ*VIX*	0.0826	0.0395	Δ*VIX*	0.0828	0.0399
	(19.50)	(11.01)		(19.47)	(11.14)
Δ*VIX_LargeSup*	0.0878	0.0399	Δ*VIX_LargeSup*	0.0878	0.0401
	(19.65)	(9.68)		(19.59)	(9.67)
Δ*VIX_SmallSup*	-0.0330	-0.0099	Δ*VIX_SmallSup*	-0.0332	-0.0102
	(-5.39)	(-2.07)		(-5.42)	(-2.13)
CusRet	-0.0058	-0.0170	*CusRet*	-0.0057	-0.0167
	(-2.15)	(-2.28)		(-2.11)	(-2.18)
SupRet	-0.1024	-0.0999	*SupRet*	-0.1024	-0.1002
	(-20.42)	(-10.50)		(-20.45)	(-10.50)
SupBeta	-0.0001	-0.0027	*SupBeta*	-0.0001	-0.0026
	(-0.25)	(-3.54)		(-0.26)	(-3.47)
LogSupMV	-0.0002	-0.0014	*LogSupMV*	-0.0002	-0.0013
	(-1.62)	(-5.16)		(-1.49)	(-4.95)
LogSupBM	0.0010	0.0004	*LogSupBM*	0.0010	0.0005
	(3.56)	(0.77)		(3.61)	(0.93)
Fixed effects			Fixed effects		
Customer	Yes	Yes	Customer	Yes	Yes
Year	Yes	Yes	Year	Yes	Yes
R-squared	4.8%	6.0%	R-squared	4.8%	6.0%
#obs	190,325	64,116	#obs	190,325	64,116