Journal of Risk **22**(5), 83–113
DOI: 10.21314/JOR.2020.434

Research Paper

Volatility spillover along the supply chains: a network analysis on economic links

Theo Berger[1] and Ramazan Gençay

[1] Department of Business and Adminsitration, University of Bremen, Enrique-Schmidt-Straße 1, 28359 Bremen, Germany; email: thberger@uni-bremen.de

(Received January 11, 2019; revised and accepted October 10, 2019)

ABSTRACT

We introduce a financial network approach to quantify the impact of counterparty risk on firms' daily market risk, measured via conditional volatility. Translating conditional volatility into a value-at-risk (VaR) framework allows us to identify extreme losses beyond an estimated loss limit and to determine volatile market regimes. We find that suppliers are exposed to additional fundamental risks that are not captured by their market beta, and these get transferred along supply chains. The identified risk spillover affects both the coverage and the quality of suppliers' market risk assessments. If customers experience large losses beyond their individual VaR limit, suppliers' variance forecasts increase by (up to) 1%, and the probability of suppliers' extreme losses doubles the next day.

Keywords: customer–supplier links; volatility spillover; value-at-risk forecasts; idiosyncratic volatility.

Corresponding author: T. Berger

Print ISSN 1465-1211 | Online ISSN 1755-2842

1 INTRODUCTION

Listed firms experience volatile stock returns and time-varying market regimes. As financial volatility measurement has important implications for applied risk management, it is crucial to understand the underlying dynamics of uncertainty.[1]

This paper introduces a customer–supplier network and deals with the empirical impact of customers' fundamental risk on suppliers' volatility. Based on published US accounting data, we identify customer–supplier relations that allow us to analyze the existence of risk spillover along supply chains. Translating firms' conditional volatility into value-at-risk (VaR) is an adequate economic approach to translating conditional volatility into listed companies' market risk. It also enables us to economically quantify the additional significant monetary loss of customers' market risk for suppliers.[2]

Schwert (1989) presents an empirical analysis of the impact of macroeconomic factors on monthly volatility of stock returns.[3] Mele (2007) adds to this finding and emphasizes the predictive power of variables that describe time-varying risk premiums, while Paye (2012) analyzes the predictive power of variables that are linked to macroeconomic uncertainty to improve volatility forecasts. Christiansen *et al* (2012) provide a thorough analysis of competing determinants of financial return volatility, covering eighty years of data and different asset classes. They point out that determinants vary by asset class and that an economic discussion on volatility predictability should be held separately from discussions on return predictability. Also, Herskovic *et al* (2016) point out that, after controlling for common variation in stock returns, residual return volatility is characterized by the same volatility structure as total returns.

As the market risk of a listed firm is mainly measured in terms of the conditional volatility of univariate return series, recent studies do not take the economic impact

---

[1] Although econometric modeling of time-varying financial volatility describes an ongoing discussion, analyses on the underlying economic factors that drive firm volatility are still sparse (see Kelly *et al* 2013). For an econometric survey on conditional volatility, we refer the reader to Engle *et al* (2013) and the references therein.

[2] Generally, VaR describes the concept of translating an assets' conditional volatility into a monetary loss limit for a given holding period; it is arguably the single most prevalent financial risk measure used in financial risk management today (see Berkowitz *et al* 2011). Please note that we exclusively apply VaR to translate conditional volatility into monetary loss limits. Our study does not aim to find the optimal econometric VaR approach for individual companies.

[3] Schwert (1989) investigates macroeconomic volatilities, economic activities and leverage.

of spillover factors into account.[4] Due to the implicit assumption that relevant factors are exclusively embedded in suppliers' own past volatility, potential spillovers from customers' volatility have not been adequately assessed. In addition, as financial volatility can be decomposed into fundamental and idiosyncratic components (see Campbell *et al* 2001; Herskovic *et al* 2016), the identification of spillover effects between customers and suppliers describes a sensible way of capturing both spillover channels effectively.

In this vein, economic links between companies that are bound to the International Financial Reporting Standards (IFRS) can be unveiled via disclosed accounting data. According to the Statement of Financial Accounting Standards (SFAS) No. 131, US companies are obliged to disclose any customers that account for more than 10% of their total annual sales. Based on disclosed data, Hertzel *et al* (2008) find evidence of customer defaults having a significant impact on the default probability of a firm. The authors indicate the existence of spillover within a customer–supplier framework of US listed companies. Cohen and Frazzini (2008) underline the information on existing customer–supplier links and present the relevance of publicly available information for the prediction of a firm's monthly future returns. Gençay *et al* (2015) use this information about customer–supplier relations and set up a network autoregressive moving average approach to analyze the impact of counterparty risk on weekly corporate credit spreads. Kelly *et al* (2013) also provide a thorough assessment of annual firm volatility in granular networks and argue that shocks are transmitted upstream from customers to suppliers.

In this paper, we add to the discussion on shocks transmitted from customers to suppliers and study the effects of competing explanatory variables on daily financial volatility. Moreover, we translate conditional volatility into a daily VaR framework to provide an economic interpretation of extreme losses and to emphasize the relevance of our findings for applied risk management.[5] Also, the applied VaR framework enables us to backtest the quality of VaR forecasts in order to distinguish between calm and volatile periods. As a result, we provide empirical evidence for the existence of risk spillover within a customer–supplier network. Further, we decompose financial volatility into fundamental and idiosyncratic components to provide an in-depth analysis of the identified spillover effects.

---

[4] In order to model volatility spillover, Engle and Kroner (1995) expand the classical generalized autoregressive conditional heteroscedasticity (GARCH) approach and assess the impact of volatility spillover via a multivariate GARCH approach (BEKK). However, as the methodological approach becomes infeasible for more than five assets, the BEKK approach has limited power for large portfolios.

[5] As demonstrated by Adrian and Brunnermeier (2016), among others, VaR provides us with an adequate tool to analyze market risk and enables us to study the impact of customers' volatility with respect to regulatory market risk assessment.

Hence, we apply the spillover framework as introduced by Gençay *et al* (2015). Our work contributes to the studies of Hertzel *et al* (2008). As described by Gençay *et al* (2015), we apply an economic network approach and identify firms' customers based on information disclosed by SFAS No. 131, constructing a customer–supplier network. In contrast to Gençay *et al* (2015), we focus on volatility transmission and identify volatility spillover effects along supply chains. Based on the identified network structure, we provide an economic assessment of determinants of daily VaR forecasts, with an emphasis on economic spillover effects, and we demonstrate the economic relevance of financial additional loss value within an applied daily risk measurement framework. As VaR describes an applied risk figure that is defined by regulatory standards, the application of a VaR framework allows for an assessment of the dimension of customers' VaR forecasts on a firm's VaR forecasts as well as an assessment of spillover effects that arise from extreme negative losses, defined as exceedances of the expected VaR limits. In addition, the identified spillovers are in line with the underlying idea of Kelly *et al* (2013). Based on daily data, we control for economic factors and provide evidence for the existence of risk spillovers between customers and suppliers. Further, in accordance with Bekaert *et al* (2012), we decompose customers' volatility into fundamental and idiosyncratic volatility to identify additional fundamental risk factors that get transferred along supply chains.

Also, we expand the methodological setup of Gençay *et al* (2015) to a binary choice approach and assess the impact of explanatory variables on the quality of a firm's VaR forecast, which is evaluated in terms of a binary variable that indicates if realized returns are beyond the expected VaR.

Our results provide evidence of significant risk spillovers within customer–supplier frameworks. Controlling for company characteristics, companies that are exposed to market risk are also exposed to significant risk spillovers. We find that customers' extreme negative losses have a statistically significant impact on the probability of a supplier's VaR exceedance. The decomposition of customers' volatility into idiosyncratic and fundamental volatility components suggests that suppliers are exposed to additional fundamental risks that are not captured by their market beta.

The remainder of this paper is organized as follows. The concept of the applied customer–supplier network and the VaR framework are introduced in Section 2. Section 3 presents the data and Section 4 contains our main empirical results. Section 5 concludes.

2 METHODOLOGY

In this section, we introduce the notation used throughout the paper, define the desirable properties of VaR, specify the adjacency matrix required to model a customer–supplier network and present our regression settings.

2.1 Value-at-risk

We translate financial conditional volatility into a standardized VaR framework to identify the different characteristics of risk spillover. Specifically, the assessment of risk spillover within a standardized VaR universe allows us to assess effects stemming both from daily changes in market risk (changes in conditional volatility) and from daily extreme losses (negative returns beyond the expected VaR limit). In addition, due to the fact that the quality of VaR forecasts can be evaluated by regulatory standards, namely regulatory backtesting, we assess the historical amount of misspecified VaR forecasts to identify changes in volatility regimes. For a thorough introduction to VaR backtesting and the regulatory traffic light approach, we refer the reader to Jorion (2007) and the references therein.

Generally, VaR defines a maximum loss limit for the underlying daily return series that will not be exceeded, with a given probability for a predefined holding period. In this study, we calculate VaR via the RiskMetrics approach and discuss a holding period of one day.[6] Let the VaR of firm i on day t ($\mathrm{VaR}_{i,t}$) be defined as

$$\mathrm{VaR}_{i,t|t-1} = -z_\alpha \sqrt{\hat{\sigma}^2_{(\mathrm{RM})i,t|t-1}}, \tag{2.1}$$

with

$$\hat{\sigma}^2_{(\mathrm{RM})i,t|t-1} = 0.94\hat{\sigma}^2_{(\mathrm{RM})i,t-1|t-2} + 0.06r^2_{t-1}. \tag{2.2}$$

Here, z_α is a quantile of order α of the normal distribution and $\hat{\sigma}^2_{(\mathrm{RM})i,t|t-1}$ is the expected conditional RiskMetrics volatility at time t of the underlying asset i.[7] The RiskMetrics approach assumes that conditional volatility follows a persistent process that is similar to a GARCH(1,1) process; however, the parameters are determined by JP Morgan and present estimated average values for daily stock price volatility (see Jorion 2007).

2.1.1 Daily changes in market risk

To identify the impact of customer–supplier spillover on a firm's daily market risk forecasts, we focus on how much the firm's conditional volatility, measured in terms of VaR forecasts, changes within two consecutive days ($\Delta\mathrm{VaR}_{i,t}$). Therefore, we

[6] Again, our study does not aim to find the optimal econometric VaR approach for each individual company. As we assess the daily VaR forecasts of 594 companies, we assume that all companies apply the RiskMetrics approach, as suggested by JP Morgan. For the sake of simplicity, we assume normally distributed returns. We refer the reader to Jorion (2007) for a thorough introduction to VaR, and to Angelidis *et al* (2004) and Haas and Pigorsch (2009) for a survey on optimal VaR modeling.

[7] In the remainder of this paper, in line with current literature (see Ziggel *et al* 2014; Siburg *et al* 2015; Halbleib and Pohlmeier 2012), we assess VaR forecasts for a holding period of $h = 1$ day. We deal with daily data and assume $E[r_t] = 0$.

focus on the changes between individual VaR forecasts from time $t-1$ to time t and define the relative change of a VaR forecast of company i at time t as

$$\Delta \mathrm{VaR}_{i,t|t-1} = \log\left(\frac{\mathrm{VaR}_{i,t|t-1}}{\mathrm{VaR}_{i,t-1|t-2}}\right). \tag{2.3}$$

In this framework $\Delta\mathrm{VaR}_{i,t|t-1}$ is exclusively affected by changes in $\hat{\sigma}^2_{(\mathrm{RM})i,t|t-1}$ and therefore provides an adequate proxy to quantify the impact of volatility spillover.[8]

2.1.2 Extreme losses

In addition to the assessment of daily changes in market risk, we apply the introduced VaR setup to provide an economic definition of unexpected extreme returns in order to study the impact of potential risk spillover stemming from unexpected losses. We define negative returns beyond the respective VaR limit as VaR breaches.[9] Let a VaR breach of company i at time t be defined by $\mathrm{Hit}_{i,t}$:

$$\mathrm{Hit}_{i,t} = I(r_{i,t} < -\mathrm{VaR}_{i,t|t-1}). \tag{2.4}$$

In this setup, I presents a binary indicator variable that equals $I = 1$ if a breach occurs and $I = 0$ otherwise. In this context, a VaR breach of firm i at time t is defined by a return of firm i at time t that is lower than the expected loss limit at time t ($\mathrm{VaR}_{i,t|t-1}$).

2.1.3 Volatility regime

Another useful property of the applied VaR setup is that the quality assessment of VaR directly relates to the assessment of the binary "Hit" variable. Thus, we draw on the intuition of regulatory quality assessment of daily VaR forecasts via backtesting and analyze the number of VaR breaches within a predefined period. That is, we apply statistical backtesting to past VaR forecasts in order to identify tumultuous market regimes, which are characterized by having an increased number of VaR breaches. According to Christoffersen (1998), a series of $(1-\alpha)\%$ VaR forecasts can be characterized as precise if

$$E[\mathrm{Hit}] = \alpha \tag{2.5}$$

holds for $0 \leqslant \alpha \leqslant 1$. That is, for a series of 95% VaR forecasts, we expect 5% of the returns to be lower than the corresponding VaR forecasts. Analogous to the

[8] This idea is inspired by the study of Adrian and Brunnermeier (2016), who research the relative difference between the systemic risk measure of a firm and its respective VaR forecast.

[9] We apply the standardized VaR framework based on the assumption of normally distributed returns in order to provide an economic intuition for extreme returns. We do not aim at finding the optimal return distribution for every individual asset.

regulatory traffic light approach (see Jorion 2007), we track the periodical quality of past VaR forecasts using the following indicator function:

$$\mathrm{Qual}_{i,t} = I\left(\sum_{j=1}^{T} \mathrm{Hit}_{i,t-j} > \lambda\right). \tag{2.6}$$

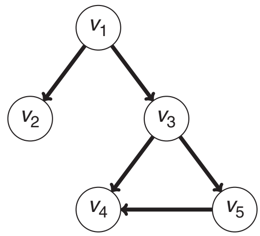
Here, λ describes the critical value and $\mathrm{Qual}_{i,t}$ takes a value of 1 if the sum of past T VaR forecasts is higher than a predefined threshold λ. In our study, we assess 95% VaR forecasts and assess a period that comprises three months ($T = 100$) in order to account for mid-run volatility regimes.[10] In order to approximate the critical values of the statistical backtesting procedures as described by Christoffersen (1998), we set $\lambda = 10$. For 95% VaR and 100 observations, ten misspecifications lead to a rejection of the VaR approach based on unconditional coverage criteria. For an overview of critical rejection rates, we refer to Jorion (2007). Hence, Qual_t indicates an amount of VaR breaches which is twice as high as the expected amount (in the past 100 days) that would lead to a rejection by statistical backtesting. This allows us to identify periods that are characterized by an inadequate number of VaR breaches. Keeping in mind that the assumption of normally distributed returns describes the underlying assumption of the applied VaR setup (see (2.1)), $\mathrm{Qual}_{i,t}$ indicates the return regime of firm i, which is more volatile than suggested by VaR forecasts based on the assumption of normally distributed returns. Specifically, if returns have deviated more strongly than suggested by a standardized VaR framework within the past three months, the introduced $\mathrm{Qual}_{i,t}$ function identifies deviations from the assumption of normally distributed returns and therefore indicates a market regime described by leptokurtosis. Tracking the sum of historical VaR breaches allows us to identify the impact of a customer's risk regime over the past three months on a supplier's VaR forecast.

2.2 Customer–supplier networks and adjacency matrixes

To model customer–supplier links, we apply a network approach, as presented by Gençay *et al* (2015). In this vein, customer–supplier networks can be adequately described by networks that are generally understood as collections of firms (nodes) and their economic relationships in the customer–supplier chain (links). According to Allen and Babus (2009), entities can be described by nodes and relations between entities can be described by links.

[10] $T = 100$ is an adequate indicator for mid-run regimes. From our point of view, the focus on $T = 100$ results in less volatile indicators than a monthly assessment ($T = 22$) and more dynamic indicators than an annual assessment ($T = 250$).

FIGURE 1 An example of a customer–supplier network.



Companies are described by $v_i = 1, \ldots, 5$ and economic links are indicated by an arrow. The direction of the arrow provides information about the flow of output. In this example, company 1 is a supplier of company 2 and company 3, and company 3 is a customer of company 1 and a supplier of firm 4 and firm 5.

Within a customer–supplier network, each company i is described by node i, and a customer–supplier relation between company i and company j is indicated by a link between nodes i and j. Following this approach leads to a network structure that can be characterized by an adjacency matrix G. Specifically, G describes a square matrix, its dimension being the number of nodes (ie, companies) in the network. However, each element of G in the ith row and jth column, $(G)_{i,j}$, takes a value of 1 if and only if there exists a customer–supplier relation between company i and company j, and a value of 0 otherwise.

Figure 1 provides an example of a customer–supplier network. For instance, there exists a customer–supplier relation between company 1 and company 2, and the arrow indicates the flow of output from company 1 to company 2. Here, company 1 is defined as a supplier for company 2; thus, company 2 is a customer of company 1. The respective G matrix capturing the structure of this network is then given by

$$G = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}. \tag{2.7}$$

In this setup, the ith row of matrix G captures the customers of company i. For instance, the third row of G refers to company 3 and indicates that company 4 and company 5 are customers of company 3. Due to the fact that the presented adjacency matrix describes economic links by values that are either 0 or 1, this matrix is characterized as unweighted.

In order to adequately capture customer–supplier spillover via a network approach, it is economically useful to indicate the strength of each economic link to account for the importance of individual customers. In this study, we expand the unweighted adjacency matrix, introduce stochastic weights to each link and allow for different weights among customers:

$$G = \begin{bmatrix} 0 & 0.4 & 0.6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9 & 0.1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \end{bmatrix}. \tag{2.8}$$

Again, G exemplifies customer–supplier relations as presented in Figure 1; however, in its current form, the sum of the elements of each row adds up to 1, and G can be described as a weighted G matrix. Here, the third row of G indicates that economic ties between supplier company 3 and customer company 4 are stronger (0.9) than between customer company 3 and supplier company 5 (0.1). Thus, company 4 accounts for 90% and company 5 accounts for 10% of potential spillover.

2.2.1 Basic properties of the network autoregressive moving average (NARMA) approach

To further understand the concept of the adjacency matrix in the context of economic links, let x be an n-dimensional vector of node characteristics that captures some properties of node i, while G describes the respective $n \times n$ adjacency matrix. In our setup, n refers to the number of companies $i, \dots, n$. Then, as introduced in Gençay *et al* (2015), spillover effects can be modeled via a NARMA process of order p and q (NARMA(p, q)):

$$y = \sum_{i=1}^{p} \alpha_i G^i y + \sum_{j=0}^{q} \beta_j G^j x + \varepsilon, \tag{2.9}$$

with α_i as a real parameter and x as an $n \times k$ matrix of exogenous node characteristics, where n is the number of companies $i, \dots, n$ and k is the number of exogenous variables $1, \dots, k$. In addition, β_i is a $1 \times k$ vector of real parameters and ε is an $(n \times 1)$-dimensional vector of errors. Further, parameters p and q determine the order of customer linkages that can be assessed.

To understand the impact of the introduced weighted adjacency matrix, let $(Gx)_i$ be the sum of neighbors' characteristics for company i with N customers. Then,

$$(Gx)_i = \sum_{j=1}^{N} G_{i,j} x_j \tag{2.10}$$

is the weighted average of customers' characteristics for node i. These arguments can be easily extended to higher-order effects. That is, $(G^k x)$ contains the weighted averages of the kth-order customers' characteristics of each firm. In our paper, we focus on first-order customer linkages.

2.3 Regression setting

To study the impact of spillover within a customer–supplier network, we draw on Gençay *et al* (2015) and apply a NARMA(0,1) approach to take into account customers' characteristics by way of the network lags of the covariates. The applied regression setting is given as follows:

$$\Delta \mathrm{VaR}_{i,t|t-1} = \alpha + \beta \,\mathrm{customer}_{i,t-1} + \gamma \,\mathrm{control}_{t-1} + \varepsilon_{i,t-1}, \tag{2.11}$$

where $\Delta\mathrm{VaR}_{i,t|t-1}$ is the change in daily VaR forecast of company i between day t and day $t-1$, $\mathrm{customer}_{i,t-1}$ is a vector and comprises the constructed characteristics of customer i at time $t-1$, and $\mathrm{control}_{t-1}$ describes a vector that covers the set of applied control variables. Hence, parameters β and γ are also vectors and capture the linear impact of each variable. Via this setup, we are able to study shock transmissions from a customer–supplier network at time $t-1$ regarding the change in volatility at time $t-1$, which describes the input for $\mathrm{VaR}_{i,t}$. We define $\mathrm{customer}_{i,t-1}$ and $\mathrm{control}_{t-1}$ as follows.

- $\mathrm{customer}_{i,t-1}$ presents the vector that describes potential spillover along supply chains. It is given by

  $$\mathrm{customer}_{i,t-1} = \{(G_{t-1} \cdot \Delta\mathrm{VaR}_{t|t-1})_i, (G_{t-1} \cdot \mathrm{Hit}_{t-1})_i, (G_{t-1} \cdot \mathrm{Qual}_{t-1})_i\}. \tag{2.12}$$

  Here, for each company i, customers' market risk is measured by $(G_{t-1} \cdot \Delta\mathrm{VaR}_{t|t-1})_i$. The ith element describes the weighted average of the VaR forecasts of customers of company i. $(G_{t-1} \cdot \mathrm{Hit}_{t-1})_i$ and $(G_{t-1} \cdot \mathrm{Qual}_{t-1})_i$ describe VaR breaches and the quality of customers' VaR forecasts, respectively.

- $\mathrm{control}_{t-1}$ describes a vector that covers the set of applied control variables. We follow Andersen *et al* (2007) and Corsi (2009) by including control variables for market characteristics and asset-specific stylized facts in our model:

  $$\begin{aligned}\mathrm{control}_{t-1} &\\ = \{&\Delta\mathrm{VaR}_{i,t-1|t-2}, \mathrm{Hit}_{i,t-1}, \mathrm{RV1m}_{t-1}, \mathrm{RV3m}_{t-1}, \mathrm{RV6m}_{t-1}, \mathrm{RV12m}_{t-1},\\ &\mathrm{SP500}_{t-1}, \mathrm{VIX}_{t-1}, (\mathrm{Baa} - \mathrm{Aaa})_{t-1}, \mathrm{YC}_{t-1}, \mathrm{YC\ Slope}_{t-1}\}.\end{aligned} \tag{2.13}$$

  Here, we include the return volatility (RV) of company i as the estimator for the standard deviation, using daily returns of the company for different time horizons (one month (RV1m), a quarter year (RV3m), a half year (RV6m) and a full year (RV12m)) to capture stylized facts about financial return volatility. Moreover, due to the fact that a VaR breach at time $t-1$ leads to an increased VaR forecast at t, we also include information about the company's VaR ($\Delta\text{VaR}_{i,t-1|t-2}$) as well as the VaR breach of the previous period ($\text{Hit}_{i,t-1}$).[11]

To account for market characteristics, we follow Gençay *et al* (2015) and include the daily returns of the Standard & Poor's 500 (SP500) and the expectations of stock market volatility described by the Chicago Board Options Exchange Volatility Index (VIX). We also include the difference between the yield on Baa- and Aaa-rated corporate bonds (Baa$-$Aaa) as a measure of market credit risk and the slope of the yield curve (YC slope), ie, the difference between ten-year (YC) and two-year benchmark treasury rates, as a measure of interest rates and economic activity.

2.3.1 Probit setting

The translation of conditional volatility into a VaR universe allows us to identify extreme returns beyond the estimated VaR limit. Therefore, we characterize returns at time t, which are beyond the estimated VaR, as a "Hit" in order to study the impact of customers' variables on the probability of the occurrence of an extreme loss (beyond the VaR limit). Due to the fact that the $\text{Hit}_{i,t}$ variable offers crucial information for the regulatory quality assessment of VaR forecasts, the transformation of variance into VaR provides an economic definition of unexpected extreme losses. Via the introduced VaR framework, we are able to characterize returns at time t as extreme losses (returns beyond the predicted VaR) or not. Hence, we also expand the introduced regression analysis to a binary choice panel data approach in order to assess the determinants of extreme losses beyond VaR limits. Specifically, we investigate the impact of spillovers within a customer–supplier network on the probability that an unexpected extreme loss, a VaR breach, occurs ($P(\text{Hit}_{i,t}=1)$) via a probit approach:

$$P(\text{Hit}_{i,t}=1)=\Phi(\alpha+\beta\ \text{customer}_{i,t}+\gamma\ \text{control}_t+\varepsilon_{i,t}). \tag{2.14}$$

Φ stands for the cumulative distribution function of the normal distribution, and $\text{customer}_{i,t}$ and control_t are as described in (2.12) and (2.13). However, as $\text{Hit}_{i,t}$ describes the variable of interest, this variable is excluded from the set of control variables control_t. In this regression setting, we are able to study the impact of customer spillover at time t on the probability of an extreme loss at time t. This setup

[11] In the remainder of this paper, for the sake of readability, we drop the subindexes of the customer matrixes and control variables.

enables us to assess information on the impact of spillover effects on the market risk assessment of the supplier.

3 DATA

We identify customer–supplier relations based on published information according to SFAS No. 131. Under SFAS No. 131, it is mandatory for companies to report any customers that account for more than 10% of total yearly sales. This data is available from COMPUSTAT's Segment Customer files. However, as customers are reported by each company manually, automatically identifying each company via standard identifiers is not straightforward. For instance, the name of a company can be misspelled, the same company can be reported under different names (eg, Ford Motor versus Ford Mtr) or a company's name can be reported with (or without) different acronyms (eg, LLC or INC). Therefore, to match the data from Reuters Datastream to reported customer–supplier links, we follow a conservative approach and exclusively consider links that describe an exact match between the reported name in Datastream (ie, Datastream local code) and an entry in the Compustat data file of names (ie, Cusip). Moreover, we exclusively assess companies that are listed over the complete sample period, and we drop those with an incomplete history of market prices. For each company, we assess the names of the customers and the total amount of sales that is reported for each customer. This information helps us determine the strength of each customer–supplier link.

The Compustat data files are comprised of 2725 different supplier names and 9863 reported customer names. Following our conservative approach allows us to identify 594 companies and 6216 links between the years 2006 and 2015. Once a link is identified, analogous to Gençay *et al* (2015), we check whether the link is valid one year prior to the reporting date. Most of the customer links are reported in December (4526 links reported) and in end-of-quarter months (1137 links reported).[12] In order to construct the weighted adjacency matrix as described in Section 2.2, we follow Gençay *et al* (2015) and weight each customer link by the sales stemming from the respective customer, normalized by the total amount of identified sales (as reported by the supplier) of the relevant year.[13]

Table 1 presents the descriptive statistics of the identified companies. The average daily 95% VaR equals 3.2%, its average daily changes (ΔVaR) are close to 0

[12] Although we allow for a dynamic customer–supplier network, the network is slowly varying.

[13] We are aware of the fact that the conservative approach allows us to achieve an approximation of customer-sales relations. Specifically, the identified weights might change if more customers are identified. Therefore, we have also assessed a nonweighted adjacency matrix, as presented in (2.7), and the significance of the results does not differ remarkably.

TABLE 1 Summary statistics.

	Mean	SD	Min	Max
95% VaR	0.031	0.014	0.000	0.599
ΔVaR (%)	−0.003	0.068	−0.031	7.601
($G \cdot \Delta$VaR) (%)	0.000	0.041	−0.031	2.345
($G \cdot$ Hit)	0.027	0.153	0	1
($G \cdot$ Qual)	0.080	0.256	0	1
Hit$_i$	0.049	0.217	0	1
RV1m	0.031	0.028	0.000	1.663
RV3m	0.031	0.027	0.000	1.223
RV6m	0.032	0.026	0.000	0.863
RV12m	0.033	0.025	0.006	0.627
VIX	20.382	9.831	0.000	80.860
SP500 (%)	0.018	0.013	−0.095	0.110
Baa − Aaa	1.168	0.540	0.530	3.500
Yield curve	3.116	1.026	1.430	5.260
YC slope (10–2)	1.615	0.870	−0.190	2.910

The data describes the regressors and regressand in our preliminary sample. The data has a balanced panel structure (594 companies, 2608 periods) and covers the period from January 1, 2006 to December 31, 2015 (daily frequency). "SD" stands for standard deviation. "ΔVaR" is defined as the change in the daily 95% VaR forecast. VaR is calculated via the RiskMetrics approach and is based on 500 past returns. Returns are assumed to follow a normal distribution, and "ΔVaR$_i$" is the change in the VaR forecast of company i. Customer ΔVaR – "($G \cdot \Delta$VaR)" – is constructed using a one-year centering window and the sales-weighted customer–supplier matrix (G). "Hit" describes the binary indicator variable (0 = No hit; 1 = Hit), which indicates a loss lower than the respective VaR forecast. "($G \cdot$ Hit)" is defined as the number of customer VaR breaches, and "($G \cdot$ Qual)" is defined as the quality of the customer VaR forecast. "Qual" describes a binary indicator variable that indicates if VaR forecasts were adequate (it is equal to $\sum$ Hits < 10) for the past 100 trading days. "Hit$_i$" is defined as a VaR breach by firm i, and return volatility (RV) is the estimator for the standard deviation using the daily returns of the firm for different time horizons: one month ("RV1m"), a quarter of a year ("RV3m"), half a year ("RV6m") and a year ("RV12m"). "SP500" refers to daily returns of the S&P 500 index and "VIX" refers to market volatility, measured daily by the CBOE volatility index. "Baa − Aaa" is the yield spread between Baa-rated corporate bonds and Aaa-rated corporate bonds. "Yield curve" is the ten-year benchmark treasury rate, and its slope ("YC slope") is the difference between the ten-year and two-year benchmark treasury rates.

(-0.0032%) and the average weighted customer VaR ($G\Delta$VaR(%)) is also close to 0. Comparatively, the average SP500 return equals 0.018%. The data has a balanced panel structure covering the period from January 1, 2006 to December 31, 2015 ($T = 2608$ days). The sample includes $n = 594$ companies and comprises 1 549 152 daily observations.

4 RESULTS

The regression estimates in Table 2 provide evidence that there exists a statistically and economically significant spillover between a firm's VaR forecasts and those of its customers. Estimated standard errors are as described by Driscoll and Kraay (1998)

TABLE 2 The relationship between VaR and customer–supplier linkages for different sets of control variables. [Table continues on next page.]

	Classical model			Customer spillover		
	(1)	(2)	(3)	(4)	(5)	(6)
$(G \cdot \Delta\text{VaR})$				0.011***	0.011***	0.008***
				(0.001)	(0.001)	(0.001)
$(G \cdot \text{Hit})$				0.004***	0.004***	0.010***
				(0.000)	(0.000)	(0.000)
$(G \cdot \text{Qual})$				–0.001***	–0.001***	–0.001***
				(0.000)	(0.000)	(0.000)
$\Delta\text{VaR}_{i,t-1\mid t-2}$	0.021***	0.021***	0.019***	0.021***	0.021***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Hit}_{i,t-1}$	0.149***	0.149***	0.153***	0.148***	0.148***	0.152***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RV1m	0.220***	0.220***	0.209***	0.221***	0.221***	0.211***
	(0.010)	(0.010)	(0.002)	(0.010)	(0.010)	(0.010)
RV3m	–0.153***	–0.153***	0.146***	–0.152***	–0.152***	–0.145***
	(0.008)	(0.008)	(0.002)	(0.008)	(0.008)	(0.007)
RV6m	–0.056***	–0.055***	–0.036**	–0.057***	–0.055***	–0.038***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
RV12m	–0.003	–0.006	–0.012	–0.004	–0.007	–0.013
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
SP500			0.374***			0.396***
			(0.006)			(0.006)

TABLE 2 Continued.

	Classical model			Customer spillover		
	(1)	(2)	(3)	(4)	(5)	(6)
VIX			0.000***			0.000***
			(0.000)			(0.000)
Baa – Aaa			−0.004***			−0.005***
			(0.000)			(0.000)
Yield curve		0.000	0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
YC slope (10–2)		−0.000	−0.000		0.000***	−0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
Constant	−0.007***	−0.008***	−0.007***	−0.007***	−0.009***	−0.007***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firms	594	594	594	594	594	594
T	2608	2608	2608	2608	2608	2608
R^2	0.22	0.22	0.23	0.22	0.22	0.23

$^{***}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$. $\Delta\text{VaR}_{i,t|t-1} = \alpha + \beta\,\text{customer}_{i,t-1} + \gamma\,\text{control}_{t-1} + \varepsilon_{i,t-1}$. $\text{customer}_{i,t}$ comprises $(G \cdot \Delta\text{VaR})$, $(G \cdot \text{Hit})$ and $(G \cdot \text{Qual})$ for customer i at time t, and control_t covers a set of various control variables. A detailed description of all variables is given in Table 1. The data has a balanced panel structure covering the period from December 1, 2006 to December 31, 2015 ($T = 2608$ days) and $n = 594$ firms, giving 1 549 152 daily observations. Numbers in parentheses are the heteroscedasticity-robust (Driscoll–Kraay) standard errors.

and are robust to intertemporal and cross-sectional dependence as well as heteroscedasticity. Further, the estimated coefficients of the applied control variables are in line with economic theory (see, for instance, Paye 2012; Christiansen *et al* 2012), and the adjusted R^2 is similar to the VaR study by Adrian and Brunnermeier (2016).

Table 2 presents the regression estimates for different sets of control variables (1)–(6) for the full sample. The results of models (4), (5) and (6) suggest that customer spillover is a statistically significant explanatory variable of a company's VaR forecast. If customers' average daily VaR forecasts ($G \cdot \Delta\text{VaR}$) increase by one standard deviation ($\sigma_{G \cdot \Delta\text{VaR}} = 0.041$) and all other explanatory variables are kept constant, a supplier firm's ΔVaR increases by 0.0328 percentage points ($\approx 0.008 \times 0.041 \times 100$pp).[14] For instance, if we suppose an investment of US\$3 125 000, its daily average VaR limit equals US\$100 000 and the average rate of daily changes in VaR (ΔVaR) is US\$−3.17 (−0.00317%). Then, an increase in customers' average daily VaR forecasts by one standard deviation increases ΔVaR to US\$29.63, holding all other parameters constant. In comparison to this, an increase in suppliers' previous VaR forecasts ($\Delta\text{VaR}_{i,t-1}$) by one standard deviation (0.068) leads to an increase in ΔVaR by up to 0.1292 percentage points ($\approx 0.019 \times 0.068 \times 100$pp) which leads to an average increase in VaR of US\$126.03. Moreover, suppliers' ΔVaR increases by 1.00 percentage point ($\approx 0.010 \times 1 \times 100$pp) to US\$996.83 when firms' customers experience large losses beyond the estimated VaR limit ($G \cdot \text{Hit} = 1$), holding other variables constant. Further, it comes as no surprise that the main impact on suppliers' ΔVaR can be explained by an increase in their "Hit" variable, which leads to an increase in ΔVaR of up to US\$15 186.92 ($\approx 0.152 \times 100\text{pp} = 15.20\text{pp}$).

Consequently, we find that changes in customers' market risk increase suppliers' VaR forecasts. Based on daily averages, 0.1292% of naive VaR is added to firms' VaR if customers' VaR increases by one standard deviation, and another 1.0% is added if the customer experiences large losses beyond the expected daily VaR limit. On top of this, significant spillover exists between customers' VaR quality and suppliers' future VaR forecasts, and the size of the respective parameters is comparable to those from the YC and the VIX. The negative sign of ($G \cdot \text{Qual}$) indicates that the sudden impact of suppliers' VaR breaches decreases in the long run and leads to declining VaR forecasts.

Across all models, we find that customer–supplier links have a statistically significant impact on suppliers' market risk (measured in terms of conditional volatility). Specifically, we identify a statistically significant impact stemming from customers' extreme losses ($G \cdot \text{Hit}$) and changes in suppliers' past VaR forecasts ($\Delta\text{VaR}_{i,t-1}$).

[14] The applied standard deviations are presented in Table 1 and the applied β refer to model (6) of Table 2.

Therefore, the results provide evidence that additional risk gets transferred along supply chains.

4.1 Risk spillover in different subperiods

Due to the fact that the underlying sample contains different market regimes (ie, market turmoil in 2008 followed by historically low interest rates until 2015), we assess the stability of the parameters that capture risk spillover in different subsamples. We divide our sample into three different subsamples that possess similar numbers of days.

- The first subsample ranges from January 1, 2006 to May 29, 2009 and covers the US recession and the market turmoil after Lehman Brothers filed for bankruptcy.[15]
- The second subsample covers two-and-a-half years after the recession and ranges from June 1, 2009 to September 12, 2012, the day before the Fed announced its third round of quantitative easing (QE3).
- The third subsample covers the time from September 13, 2012 to the end of December 2015.

The three different subsamples describe changing market conditions that are characterized by similar lengths but by different risk-return scenarios. Measured using SP500 and VIX, the average market returns of SP500 and the average VIX from 2006 to 2009 are −0.039% and 23.57, respectively. This period includes the financial turmoil after Lehman Brothers filed for bankruptcy. Thus, this subperiod allows for an assessment of spillover effects when markets are defined by a collective downturn. The post-recession period from 2009 until 2012 is characterized by positive average returns (0.057%) and a decreased average VIX (22.17), and it is affected by potential spillovers from the European debt crisis. As this period covers a collective market upswing, the impact of rising market regimes can be assessed. The period from 2012 to 2015 is characterized by having a similar length but decreased average returns (0.040%) and a decreased average VIX (15.13). This sample does not include a collective market down- or upswing, or offer a sensible subperiod to reconcile its findings with the results of the other two subperiods.

Table 3 gives the regression results for the different subsamples. We find the average spillover stemming from customers' VaR forecasts to suppliers' VaR forecasts is exclusively significant during the market turmoil of 2007 until May 2009. This finding can be explained by the idea of contagion, as reported by Forbes and Rigobon

[15] According to the National Bureau of Economic Research (NBER), the US recession ended in June 2009.

TABLE 3 The relationship between VaR and customer–supplier linkages for three different subperiods.

	Subperiods			
	2006–9	**2009–12**	**2012–15**	**Total**
$(G \cdot \Delta\text{VaR})$	0.013***	0.003	0.005*	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)
$(G \cdot \text{Hit})$	0.009***	0.014***	0.008***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)
$(G \cdot \text{Qual})$	−0.001***	−0.002***	−0.001*	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta\text{VaR}_{i,t-1\mid t-2}$	0.020***	0.012***	0.016***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Hit}_{i,t-1}$	0.150***	0.148***	0.159***	0.152***
	(0.000)	(0.000)	(0.001)	(0.001)
RV1m	0.210***	0.162***	0.306***	0.211***
	(0.016)	(0.017)	(0.017)	(0.010)
RV3m	−0.157***	−0.099***	−0.205***	−0.145***
	(0.013)	(0.010)	(0.013)	(0.007)
RV6m	−0.026	−0.036	−0.059**	−0.038***
	(0.032)	(0.014)	(0.019)	(0.011)
RV12m	−0.009	−0.011	−0.021	−0.013***
	(0.035)	(0.011)	(0.018)	(0.010)
SP500	0.305***	0.514***	0.651***	0.396***
	(0.006)	(0.010)	(0.014)	(0.006)
VIX	0.000***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Baa − Aaa	−0.005***	−0.011***	−0.004***	−0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Yield curve (10–2)	0.000	0.003***	−0.003***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
YC slope	−0.000	−0.006***	0.003***	−0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Constant	−0.006***	0.006***	−0.010***	−0.007***
	(0.001)	(0.001)	(0.000)	(0.000)
Firms	594	594	594	594
T	919	839	850	2608
R^2	0.234	0.227	0.231	0.230

$^{***}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$. $\Delta\text{VaR}_{i,t\mid t-1} = \alpha + \beta\,\text{customer}_{i,t-1} + \gamma\,\text{control}_{t-1} + \varepsilon_{i,t-1}$. $\text{customer}_{i,t-1}$ comprises $(G \cdot \Delta\text{VaR})$, $(G \cdot \text{Hit})$ and $(G \cdot \text{Qual})$ for customer i at time $t-1$, and control_{t-1} covers the set of control variables as presented by (6) in Table 2. A detailed description of all variables is given in Table 1. The data has a balanced panel structure and the subperiods cover the periods from January 1, 2006 to May 29, 2009, from June 1, 2009 to September 12, 2012, and from September 13, 2012 to December 31, 2015. The numbers in parentheses are the heteroscedasticity-robust (Driscoll–Kraay) standard errors.

(2002). That is, turbulent market times are typically characterized by joint downturns, which result in an increased interdependence between individual assets. Consequently, in comparison to the results of the full sample (see Table 1), the average ΔVaR is positive and equals 0.036%. Holding other variables constant, an increase in customers' VaR ($G \cdot \Delta$VaR) by one standard deviation (0.038) increases suppliers' daily average ΔVaR by 0.049 percentage points ($\approx 0.013 \times 0.038 \times 100$pp) during the period from 2006 to 2009.[16] In comparison to the findings of the previous section, for a hypothetical US\$100 000 VaR limit, ΔVaR increases up to US\$87.00, which is more than twice as high as reported in Table 2. However, the stronger impact of additional counterparty risk spillover is mainly driven by the larger average of ΔVaR, which is caused by the collective market downturn in 2008.

Further, the fact that changes in customers' VaR provide an insignificant explanatory variable of suppliers' VaR forecasts during 2009–12 and 2012–15 indicates that significant average spillovers arise from the collective market downturns after September 12, 2008.[17] Therefore, average spillovers stemming from daily changes in ΔVaR seem to be exclusively present in market periods that are defined by collective market downturns.

Across all periods, the extreme negative returns ($G \cdot$ Hit) and ($G \cdot$ Qual) describe a significant impact on suppliers' VaR forecasts, and the estimated coefficients are similar to the discussed coefficients of Table 2.

4.2 Risk spillover with respect to company characteristics

To assess the relevance of company characteristics to the existence of risk spillover within a customer–supplier network, we draw on Fama and French (1996) and consider the Fama–French three-factor model to categorize the assessed companies according to individual company characteristics.[18]

According to Fama and French (1996), the return of company i at time t can be explained by the excess return on the market (MKT), the average return on small portfolios minus the average return on big portfolios (SMB) and the average return on value portfolios minus the average return on growth portfolios (HML):

$$r_{i,t} = \beta_{0,i,t} + \beta_{1,i,t}\mathrm{MKT}_t + \beta_{2,i,t}\mathrm{SMB}_t + \beta_{3,i,t}\mathrm{HML}_t + u_{i,t}. \qquad (4.1)$$

[16] Due to page constraints, descriptive statistics of the different subperiods are available upon request.

[17] This is the day Lehman Brothers filed for bankruptcy.

[18] For a thorough introduction to the Fama–French three-factor approach, we refer the reader to Fama and French (2015) and the references therein.

TABLE 4 The relationship between customer–supplier linkages and Fama–French three-factor characteristics. [Table continues on next page.]

(a) Firms sorted by market beta

	–0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.006	0.0121***	0.008***	0.009***
	(0.005)	(0.004)	(0.002)	(0.003)
$(G \cdot \text{Hit})$	0.002	0.0051***	0.011***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
$(G \cdot \text{Qual})$	0.000	–0.001	–0.002***	–0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Firms	55	84	324	111
T	2608	2608	2608	2608
R^2	0.194	0.214	0.236	0.260

(b) Firms sorted by small minus big

	0<SMB<0.3	**0.3<SMB<0.7**	**0.7<SMB<1.3**	**1.3<SMB**
$(G \cdot \Delta\text{VaR})$	0.013***	0.005**	0.008**	0.012***
	(0.003)	(0.002)	(0.003)	(0.002)
$(G \cdot \text{Hit})$	0.009***	0.008***	0.012***	0.017***
	(0.001)	(0.000)	(0.001)	(0.001)
$(G \cdot \text{Qual})$	–0.001*	–0.001***	–0.001**	–0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
Firms	102	337	103	47
T	2608	2608	2608	2608
R^2	0.193	0.231	0.254	0.296

Here, the variable MKT is the excess return on the market portfolio (market beta), SMB is the size factor and HML is the value factor.[19] For each company i, we estimate the individual β for the full sample and categorize the assessed companies by market beta ($\beta_{1,i,t}$), SMB factor ($\beta_{2,i,t}$) and HML factor ($\beta_{3,i,t}$). Further, we define large-cap and small-cap companies (indicated by SMB factors close to 0 and close to 1) into value and growth stocks (identified by HML factors close to 0 and close to 1) and into near-zero-beta and near-one-beta firms (identified by an MKT factor). Further, we consider companies that are characterized by having factors neither close to 0 nor close to 1 as an additional group; this is in order to avoid the results being

[19] We obtained this data from Kenneth French's homepage: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

TABLE 4 Continued.

(c) Firms sorted by high minus low

	−1.0<HML<−0.3	**−0.3<HML<0.0**	**0.0<HML<0.3**	**0.3<HML<1.0**
$(G \cdot \Delta\text{VaR})$	0.006*	0.008**	0.010***	0.005
	(0.002)	(0.003)	(0.002)	(0.003)
$(G \cdot \text{Hit})$	0.010***	0.011***	0.008***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
$(G \cdot \text{Qual})$	−0.001***	−0.002***	−0.001***	−0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Firms	167	125	235	57
T	2608	2608	2608	2608
R^2	0.236	0.240	0.227	0.230

$^{***}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$. $\Delta\text{VaR}_{i,t|t-1} = \alpha + \beta\,\text{customer}_{i,t-1} + \gamma\,\text{control}_{t-1} + \varepsilon_{i,t-1}$. A detailed description of the data and the regression setup is provided in Table 2. The Fama–French factors are the excess return on the market ("MKT"), the average return on small portfolios minus the average return on big portfolios ("SMB"), and the average return on value portfolios minus the average return on growth portfolios ("HML"). To save space, this table presents only the estimated coefficients that describe the impact of customer spillover ($\text{customer}_{i,t-1}$).

affected by the number of companies that are not adequately characterized by the chosen categories and to demonstrate the transition between the two categories.

Table 4 presents the estimated parameters of the assessed spillover components with respect to Fama–French three-factor categories. Due to the fact that the applied categorization of companies excludes companies that are characterized as outliers, the total number of companies differs by category.

The parameters of the applied control variables do not remarkably differ from the results presented in Table 3. In the remainder, we exclusively focus on the discussion of the estimated spillover parameters. We find that the beta factor indicating the responsiveness of an individual company being priced to the SP500 presents a sensitive characterization that helps us identify companies exposed to volatility spillovers stemming from their customers. Specifically, network spillovers are economically and statistically significant determinants of changes in VaR forecasts for companies that are characterized by having a beta larger than 0 (ie, $0.3 < \text{MKT} < 0.7$, $0.7 < \text{MKT} < 1.3$ and $1.3 < \text{MKT} < 1.7$). In this vein, both the sign and the magnitude of the estimated coefficients that capture customer spillover are similar to the parameters reported in Table 3. Those near-zero-beta companies that are not exposed to market risk are not significantly exposed to risk spillover. Thus, stocks that are weakly correlated to market movements (or are less risky than the SP500) are also not significantly exposed to customer spillover.

TABLE 5 The relationship between customer–supplier linkages and market beta for three different subperiods. [Table continues on next page.]

(a) 2006–9

	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.013	0.019*	0.014***	0.008
	(0.009)	(0.008)	(0.003)	(0.004)
$(G \cdot \text{Hit})$	0.004	0.004*	0.011***	0.013***
	(0.002)	(0.002)	(0.001)	(0.001)
$(G \cdot \text{Qual})$	0.000	0.000	−0.002***	−0.001
	(0.001)	(0.002)	(0.000)	(0.001)
Firms	55	84	324	111
T	919	919	919	919
R^2	0.225	0.210	0.234	0.275

(b) 2009–12

	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	−0.002	0.017*	0.003	0.005
	(0.008)	(0.009)	(0.003)	(0.005)
$(G \cdot \text{Hit})$	0.015*	0.008***	0.014***	0.020***
	(0.002)	(0.002)	(0.001)	(0.002)
$(G \cdot \text{Qual})$	−0.002	−0.001	−0.002***	−0.002*
	(0.001)	(0.001)	(0.000)	(0.001)
Firms	55	84	324	111
T	839	839	839	839
R^2	0.215	0.235	0.262	0.262

In addition, coefficients that capture the impact of extreme negative returns (indicated by $(G \cdot \text{Hit})$) are also significant for companies that are characterized by a beta larger than 0. Hence, VaR forecasts of near-zero-beta companies are not significantly exposed to the extreme negative returns of their customers.

Dividing the companies into small-cap and large-cap stocks (SMB) or into value and growth stocks (HML) does not impact the statistical significance of risk spillover. Spillovers remain stable throughout different firms' characteristics for both categories. The size of the estimated significant coefficients is comparable to those of the analysis of the full sample period.

The results suggest that the existence of risk spillover is independent of the market capitalization and the book-to-market ratio of US companies. Moreover, it is the

TABLE 5 Continued.

(c) 2012–15

	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.007	0.002	0.004	0.013
	(0.008)	(0.004)	(0.007)	(0.002)
$(G \cdot \text{Hit})$	−0.003	0.005*	0.009***	0.015***
	(0.002)	(0.002)	(0.001)	(0.002)
$(G \cdot \text{Qual})$	0.000	−0.002	−0.001**	−0.001*
	(0.002)	(0.001)	(0.001)	(0.001)
Firms	55	84	324	111
T	850	850	850	850
R^2	0.219	0.243	0.251	0.251

$^{***}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$. $\Delta\text{VaR}_{i,t|t-1} = \alpha + \beta\ \text{customer}_{i,t-1} + \gamma\ \text{control}_{t-1} + \varepsilon_{i,t-1}$. The regression setup is explained in Table 2. The market beta is the Fama–French factor that is the excess return on the market (MKT). To save space, this table presents only the estimated coefficients that describe the impact of customer spillover ($\text{customer}_{i,t-1}$). A detailed description of the data and the regression setup is provided in Table 3.

company's beta that describes a crucial attribute of identifying suppliers that are exposed to customer spillover within the empirical customer–supplier network.

4.3 Risk spillover with respect to company characteristics in different subperiods

As companies that are characterized by a market beta larger than 0.3 are significantly affected by customer spillover, analogous to Section 4.1, we assess the robustness of the results in different subperiods. Due to the findings of Section 4.2, we exclusively focus on companies' market beta factors in different subperiods.[20]

Table 5 presents the results of companies that are characterized by different beta factors in different subperiods. Similar to our discussion of the results in Table 4, we exclusively discuss the estimated spillover parameters. The main finding is that customers' market risk ($G \cdot \Delta\text{VaR}$) is not a statistically significant determinant of suppliers' market risk for near-zero-beta companies across the subsamples. Further, spillovers from changes in customers' daily VaRs are exclusively relevant in the time from 2006 to 2009 for companies that are characterized by a beta larger than 0.[21] In

[20] Categorizing companies via SMB and HML leads to similar findings, as presented in Table 4.
[21] As described in Section 4.1, the period from 2006 to 2009 contains both market turmoil and contagion.

TABLE 6 The relationship between VaR and customer–supplier linkages for three different subperiods: a probit analysis.

	Subperiods			
	2006–9	**2009–12**	**2012–15**	**Total**
$(G \cdot \Delta\text{VaR})$	0.448***	0.484***	0.275***	0.431***
	(0.070)	(0.078)	(0.065)	(0.040)
$(G \cdot \text{Hit})$	0.427***	0.382***	0.386***	0.459***
	(0.015)	(0.015)	(0.014)	(0.008)
$(G \cdot \text{Qual})$	−0.112***	−0.079***	−0.016	−0.079***
	(0.013)	(0.014)	(0.013)	(0.008)
$\Delta\text{VaR}_{i,t\mid t-1}$	0.517***	0.639***	0.618***	0.594***
	(0.036)	(0.042)	(0.036)	(0.022)
RV1m	1.603***	1.882***	2.606***	1.911***
	(0.332)	(0.0324)	(0.403)	(0.202)
RV3m	−4.931***	−2.983***	−5.894***	−4.563***
	(0.426)	(0.324)	(0.593)	(0.278)
RV6m	2.245***	−0.987*	−0.311	0.640**
	(0.435)	(0.397)	(0.587)	(0.239)
RV12m	0.418	−1.719***	3.168***	1.473***
	(0.423)	(0.234)	(0.439)	(0.174)
SP500	−21.800***	−42.090***	−48.849***	−30.990***
	(0.215)	(0.359)	(0.471)	(0.171)
VIX	0.012***	−0.010***	−0.008***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Baa − Aaa	−0.369***	−0.322***	−0.128*	−0.236***
	(0.012)	(0.031)	(0.022)	(0.007)
Yield curve	−0.101	0.092***	0.044*	−0.024***
	(0.011)	(0.024)	(0.020)	(0.000)
YC slope	−0.029	−0.199***	−0.085***	−0.035***
(10–2)	(0.007)	(0.041)	(0.022)	(0.003)
Constant	−1.059***	−1.081***	−1.081***	−1.414***
	(0.054)	(0.062)	(0.062)	(0.037)
Firms	594	594	594	594
T	919	839	850	2608
LL	−88 094.6	−79 854.8	−89 116.2	−270 829.6

*** $p < 0.001$. ** $p < 0.01$. * $p < 0.05$. $P(\text{Hit}_{i,t} = 1) = \Phi(\alpha + \beta \text{ customer}_{i,t} + \gamma \text{ control}_t + \varepsilon_{i,t})$. The data has a panel structure and covers the period from January 2006 to December 2015. This table presents the estimated probit coefficients. A detailed description of all variables is given in Table 1.

addition, extreme negative returns ($G \cdot$ Hit) are a significant determinant of changes in suppliers' VaR forecasts across the subsamples. The estimated coefficients, when significant, are comparable to the coefficients presented in Table 4.

Further, in the period 2006–9, market prices are characterized by a collective downward movement, and risk spillovers stemming from changes in customers' daily VaR forecasts are relevant for near-one-beta firms. Keeping all other variables constant, an average increase in customers' VaR forecasts ($G \cdot \Delta\text{VaR}$) leads to a remarkable increase in suppliers' average VaR forecasts by up to 0.05 percentage points.[22] Moreover, coefficients that capture spillovers stemming from negative extreme returns ($G \cdot \text{Hit}$) are significant across the market regimes, and the average impact of a customer's extreme negative return ($G \cdot \text{Hit} = 1$) increases suppliers' VaR by 1.4 percentage points.

Consequently, suppliers that are exposed to systematic market risk, indicated by their market beta factor, are also exposed to additional risk spillover.

4.4 Risk spillover and unexpected losses in different subperiods

We expand our VaR spillover analysis and assess the impact of customers' risk on the relevant information for regulatory quality assessment of daily VaR forecasts. Therefore, we investigate the impact of spillover on the realization of a VaR breach.

The applied VaR framework allows us to study not only the dimension of a firm's market risk but also the impact of extreme losses beyond the estimated VaR limit. As described in Section 2.2, a breach of the estimated VaR indicates a negative extreme return beyond the estimated quantile and provides crucial information for regulatory quality assessment. Hence, the applied VaR framework enables us to assess the impact of risk spillover within a customer–supplier network on a firm's VaR breach the next day. In order to assess spillover effects on the quality of VaR forecasts, we expand the applied network approach to a binary choice approach and assess the binary indicator variable "Hit" (a realized loss smaller than the VaR forecasts equals "no breach" and a realized loss larger than the VaR forecasts equals "breach"). Specifically, we analyze the explanatory power of spillover effects for the probability of future VaR breaches via a pooled probit approach.

Table 6 gives the results for different subperiods and the full sample. The signs of the estimated coefficients, when significant, are in line with our economic understanding.[23] Interestingly, the results indicate that risk spillover is a statistically

[22] The average change in daily VaR forecasts (ΔVaR) equals -0.003%. The relevant figures can be found in Tables 2–4.

[23] The coefficients that capture the impact of market returns (SP500) indicate that increasing market returns has a significantly negative impact on the probability of a VaR breach. In other words, the probability of a breach increases when market returns are negative. Further, the coefficients indicate that realized short-term volatility (RV1m) has a positive impact on the probability of a VaR breach, ie, an increase in short-run volatility increases the likelihood of a VaR breach, whereas an increase in mid-term volatility (RV3m) has a negative impact on the likelihood of a VaR breach. Thus, if mid-term volatility is high, the likelihood of a breach decreases. This finding indicates that daily VaR forecasts, as presented in (2.3), adjust to increased turmoil via an increased VaR limit.

TABLE 7 The relationship between customer–supplier linkages and market beta for three different subperiods: a probit analysis. [Table continues on next page.]

(a) 2006–9

	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.168 (0.232)	0.707*** (0.171)	0.474*** (0.093)	0.364* (0.175)
$(G \cdot \text{Hit})$	0.126* (0.056)	0.136** (0.047)	0.419*** (0.019)	0.507*** (0.031)
$(G \cdot \text{Qual})$	−0.089* (0.037)	−0.028 (0.034)	−0.128*** (0.018)	−0.126*** (0.029)
Firms	55	84	324	111
T	919	919	919	919
LL	−10 227.5	−14 908.0	−53 856.3	−17 990.9

(b) 2009–12

	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.392 (0.251)	0.286 (0.224)	0.575*** (0.105)	0.559** (0.175)
$(G \cdot \text{Hit})$	0.073 (0.063)	0.174*** (0.050)	0.362*** (0.020)	0.376*** (0.034)
$(G \cdot \text{Qual})$	0.017 (0.041)	−0.022 (0.039)	−0.075*** (0.019)	−0.132*** (0.034)
Firms	55	84	324	111
T	839	839	839	839
LL	−8684.3	−12 726.8	−42 704.2	−13 468.1

significant explanatory variable for VaR breaches of the supplier across the subperiods. Our main finding is that, when a customer suffers an extreme loss beyond the 95% VaR limit ($G \cdot \text{Hit} = 1$), the probability that the supplier will face an extreme loss beyond its individual VaR forecast significantly increases. That is, a customer's VaR breach ($G \cdot \text{Hit} = 1$) increases the average probability of a firm's VaR breach from 3.54% to 8.86% the next day.[24]

[24] Within a probit analysis, the magnitude of the parameters is not straightforward to interpret. Under the assumption that all other parameters remain constant, the difference between the likelihood of $G \cdot \text{Hit} = 0$ and $G \cdot \text{Hit} = 1$ describes the marginal impact of spillover effects. The applied β values are presented in Table 6 (Total) and the average values of each variable are given in Table 1.

TABLE 7 Continued.

(c) 2012–15				
	−0.3<MKT<0.3	**0.3<MKT<0.7**	**0.7<MKT<1.3**	**1.3<MKT<1.9**
$(G \cdot \Delta\text{VaR})$	0.229	0.247	0.233**	0.534***
	(0.215)	(0.177)	(0.088)	(0.145)
$(G \cdot \text{Hit})$	0.213***	0.241***	0.339***	0.539***
	(0.058)	(0.043)	(0.019)	(0.031)
$(G \cdot \text{Qual})$	0.052	−0.077*	−0.016	−0.004
	(0.044)	(0.037)	(0.018)	(0.028)
Firms	55	84	324	111
T	850	850	850	850
LL	−9260.4	−13 163.8	−48 871.8	−16 456.7

$^{***}p < 0.001$. $^{**}p < 0.01$. $^{*}p < 0.05$. $P(\text{Hit}_{i,t} = 1) = \Phi(\alpha + \beta\,\text{customer}_{i,t} + \gamma\,\text{control}_t + \varepsilon_{i,t})$. The data has a panel structure and covers the period from January 2006 to December 2015. A detailed description of all variables is given in Table 1. To save space, this table presents only the estimated probit coefficients that describe the impact of customer spillover ($\text{customer}_{i,t}$). The presented Fama–French factor describes the excess return on the market (MKT).

Similar to the impact of VaR breaches, we find that the indicator variable that describes the quality of customers' VaR forecasts ($G \cdot$ Qual) significantly affects the probability of a company having a VaR breach the next day. If customers' VaR forecasts over the last 100 days are defined by an inadequate amount of VaR breaches (larger than 10%), keeping all variables constant, the probability of a supplier's VaR breach decreases from 3.54% to 3.00%.

Comparing spillover effects stemming from $G \cdot$Hit and $G \cdot$Qual provides evidence that customers' sudden VaR breaches increase the probability of a supplier's VaR breach, whereas the probability of a supplier's VaR breach decreases if the customer has VaR violations over a longer period. This finding suggests that the quality of suppliers' VaR forecasts is exposed to customers' sudden extreme losses and adjusts to sustained customer risk.

4.5 Unexpected losses and firm characteristics

Analogous to the analysis in Section 4.3, we focus on companies that are described by different market beta factors to gain further insights into the existence of spillover effects within the empirical customer–supplier network. We also assess the impact of spillover effects on the probability of VaR breaches over time, focusing on different subsamples.

Table 7 presents the estimated spillover parameters, categorized by subperiod and companies' beta factors. Analogous to our regression analysis, in the remainder of this section, we exclusively focus on the discussion of spillover parameters.[25] The results confirm our previous findings: both the size of a customer's VaR forecasts and the occurrence of a customer VaR breach are significant explanatory variables for the probability of a firm's VaR breach for near-one-beta companies. It is remarkable that spillover effects are significant in all subperiods. The results underpin the findings of Table 5; the explanatory power of customers' characteristics remains statistically significant throughout different market periods for near-one-beta companies. Note that the dimension and the magnitude of the coefficients are similar to the effects reported in Section 4.4.

Further, the estimated coefficients do not indicate that customers' characteristics have statistically significant explanatory power for near-zero-beta companies. The findings suggest that there is no statistically significant spillover channel within the customer–supplier network for companies that are not affected by market volatility. That is, in line with the spillover analysis of Section 4.3, customers' extreme losses beyond the 95% VaR limit do not impact the probability of future extreme losses for their suppliers.

Keeping in mind that we estimate VaR forecasts under the assumption of normally distributed returns, more than 10% of VaR breaches in the last 100 days of our studied period ($G \cdot \text{Qual} = 1$) coincide with the fact that historical returns follow a leptokurtic distribution (ie, extreme losses occur more often than suggested by the tail behavior of the normally distributed returns). Thus, the results provide evidence that near-one-beta companies are affected by a potential shift in the volatility regime of their customers (indicated by ($G \cdot \text{Qual}$)).

Therefore, in line with the findings regarding changes in suppliers' VaR forecasts (see Sections 4.1–4.3), we find that near-one-beta companies are also exposed to statistically significant spillovers within a customer–supplier network. Moreover, similar to the findings in Section 4.4, the results provide evidence that the extreme losses of a customer (indicated by customers' VaR breaches) increase the average probability of a VaR breach for the supplier by around 5 percentage points.

Controlling for different firm characteristics via the Fama–French three-factor approach, we find that customer spillovers are relevant to small-cap and large-cap as well as growth and value companies. Our main finding is that companies that are exposed to systematic market risk within the applied customer–supplier network (indicated by beta) are also exposed to customer spillover. This suggests that there exists a link between customer spillover and market risk. Moreover, the results provide evidence that it is the beta factor of a supplier that determines the relevance of additional risk spillovers within the empirical customer–supplier network.

[25] A detailed overview of the regression results for all Fama–French factors and control variables is available upon request.

5 CONCLUSION

The main result of our analysis reveals that additional fundamental risk gets transferred along supply chains. Suppliers are exposed to additional fundamental risk that is not captured by their market beta. Hence, suppliers are exposed to fundamental risk not only directly but also indirectly by their customers' market beta.

In particular, we identify significant daily spillover effects from customers' VaR to suppliers' VaR within an empirical customer–supplier network that account for an additional 1% of suppliers' market risk. Decomposing customers' volatility into fundamental and idiosyncratic components corroborates that fundamental risks describe the relevant components that drive volatility spillover. We also present a novel application of financial networks to binary choice models and provide empirical evidence of the significant impact of customers' extreme losses. This impact doubles the probability of a supplier experiencing extreme losses beyond its VaR limit and is therefore crucial for regulatory VaR assessment.

Consequently, the introduced customer–supplier network describes a sensible approach to identifying risk spillover effects that impact both the size and the quality of daily VaR forecasts. Future research should focus on the application of natural language processing in order to match data from Reuters Datastream and Compustat to generate a larger sample.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

ACKNOWLEDGEMENTS

Ramazan Gençay gratefully acknowledges financial support from the Natural Sciences and Engineering Research Council of Canada and the Social Sciences and Humanities Research Council of Canada. Ramazan Gençay sadly passed away after this manuscript was completed.

REFERENCES

Adrian, T., and Brunnermeier, M. K. (2016). CoVaR. *American Economic Review* **106**(7), 1705–1741 (https://doi.org/10.1257/aer.20120555).

Allen, F., and Babus, A. (2009). Networks in finance. In *Network-Based Strategies and Competencies*, Kleindorfer, P., and Wind, J. (eds). Wharton School Publishing (https://doi.org/10.2139/ssrn.1094883).

Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007). Roughing it up: including jump components in the measurement, modeling and forecasting of return volatility. *Review of Economics and Statistics* **89**, 701–720 (https://doi.org/10.1162/rest.89.4.701).

Angelidis, T., Benos, A., and Degiannakis, S. (2004). The use of GARCH models in VaR estimation. *Statistical Methodology* **1**(1), 105–128 (https://doi.org/10.1016/j.stamet.2004.08.004).

Bekaert, G., Hodrick, R. J., and Zhang, X. (2012). Aggregate idiosyncratic volatility. *Journal of Financial and Quantitative Analysis* **47**(6), 1155–1185 (https://doi.org/10.1017/S0022109012000543).

Berkowitz, J., Christoffersen, P., and Pelletier, D. (2011). Evaluating value-at-risk models with desk-level data. *Management Science* **57**(12), 2213–2227 (https://doi.org/10.1287/mnsc.1080.0964).

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have identical stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance* **56**(1), 1–43 (https://doi.org/10.1111/0022-1082.00318).

Christiansen, C., Schmeling, M., and Schrimpf, A. (2012). A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics* **27**(1), 956–977 (https://doi.org/10.1002/jae.2298).

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review* **39**(4), 841–862 (https://doi.org/10.2307/2527341).

Cohen, L., and Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance* **63**(4), 1977–2011 (https://doi.org/10.1111/j.1540-6261.2008.01379.x).

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics* **7**(2), 174–196 (https://doi.org/10.1093/jjfinec/nbp001).

Driscoll, J., and Kraay, A. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics* **80**(4), 549–560 (https://doi.org/10.1162/003465398557825).

Engle, R. F., and Kroner, F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory* **11**(1), 122–150 (https://doi.org/10.1017/S0266466600009063).

Engle, R. F., Ghysels, E., and Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics* **95**(3), 776–797 (https://doi.org/10.1162/REST_a_00300).

Fama, E. F., and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance* **51**(1), 55–84 (https://doi.org/10.1111/j.1540-6261.1996.tb05202.x).

Fama, E. F., and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics* **116**(1), 1–22 (https://doi.org/10.1016/j.jfineco.2014.10.010).

Forbes, K. J., and Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *Journal of Finance* **57**(5), 2223–2261 (https://doi.org/10.3386/w7267).

Gençay, R., Signori, D., Xue, Y., Yu, X., and Zhang, K. (2015). Economic links and credit spreads. *Journal of Banking and Finance* **55**(1), 157–169 (https://doi.org/10.1016/j.jbankfin.2015.02.007).

Haas, M., and Pigorsch, C. (2009). Financial economics: fat-tailed distributions. *Encyclopedia of Complexity and Systems Science* **4**(1), 3404–3435 (https://doi.org/10.1007/978-0-387-30440-3_204).

Halbleib, R., and Pohlmeier, W. (2012). Improving the value at risk forecasts: theory and evidence from financial crisis. *Journal of Economic Dynamics & Control* **36**, 1212–1228 (https://doi.org/10.1016/j.jedc.2011.10.005).

Herskovic, B., Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility. *Journal of Financial Economics* **119**(2), 249–283 (https://doi.org/10.1016/j.jfineco.2015.09.010).

Hertzel, M., Li, Z., Officer, M., and Rodgers, K. (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics* **87**(1), 374–387 (https://doi.org/10.1016/j.jfineco.2007.01.005).

Jorion, P. (2007). *Value at Risk: The New Benchmark for Managing Financial Risk*, 3rd edn. McGraw-Hill, New York.

Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2013). Firm volatility in granular networks. Working Paper 19466, NBER (https://doi.org/10.3386/w19466).

Mele, A. (2007). Asymmetric stock market volatility and the cyclical behavior of expected returns. *Journal of Financial Economics* **86**(1), 446–478 (https://doi.org/10.1016/j.jfineco.2006.10.002).

Paye, B. S. (2012). "Deja vol": predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics* **106**(1), 527–546 (https://doi.org/10.2139/ssrn.783986).

Schwert, G. W. (1989). Why does stock market volatility change over time? *Journal of Finance* **44**(1), 1115–1124 (https://doi.org/10.1111/j.1540-6261.1989.tb02647.x).

Siburg, K. F., Stoimenov, P., and Weiss, G. N. F. (2015). Forecasting portfolio value-at-risk with nonparametric lower tail dependence estimates. *Journal of Banking and Finance* **54**, 129–140 (https://doi.org/10.1016/j.jbankfin.2015.01.012).

Ziggel, D., Berens, T., Weiss, G. N. F., and Wied, D. (2014). A new set of improved value-at-risk backtests. *Journal of Banking and Finance* **48**, 29–41 (https://doi.org/10.1016/j.jbankfin.2014.07.005).