Stock Return Dependence and Product Market Linkages

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Abstract

We study the implications of interfirm product market linkages for dependence among the daily stock returns of US publicly traded firms using a spatial econometric regression. Firms' stock returns are affected by those of their rivals, major customers (i.e., those that represent 10% or more of the firms' revenue), potential customers, and potential suppliers. All the effects are the strongest contemporaneously and diminish rapidly thereafter. Furthermore, the effects of rivals and major customers change with various characteristics related to the product market network. We document both a contagion effect and a competitive effect among rival firms. Positive (negative) dependence on the returns of rivals implies that the contagion (competitive) effect dominates. The competitive effect is found to dominate the contagion effect in highly concentrated industries, while the contagion effect becomes stronger in industries with higher product-market fluidity. Major customers' effect is larger for firms that depend on their major customer(s) for a larger portion of sales and whose products are similar to those of other firms. This suggests that a concentrated customer base and weak product uniqueness may lower firms' bargaining power and increase the sensitivity of their stock returns to those of large customers. Furthermore, we show that a firm's stock return is more sensitive to linked firms' negative return shocks than to their positive return shocks.

Keywords: network, return comovement, competition and contagion effects, supply chain

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1. Introduction

Firms are linked to each other in the product market. Firm-level shocks can transmit to the firm's competitors and those linked to the firm through the supply chain. Such interfirm relationships can be reflected in covariations of firms' stock returns and hence provide information for investment decisions. This paper studies the implications of interfirm product market linkages for dependence among the stock returns of US publicly traded firms. We model the contemporaneous and lagged responses of firms' daily stock returns to the returns of the portfolios including, individually, the firms' rivals, major customers, potential customers and potential suppliers, using spatial econometric techniques. We focus on the responses to rivals and major customers and analyze how they depend on the structure of the product market and firms' characteristics in the product market network.

This paper is related to the literature that studies intra-industry information transfer and extreme credit events. Lang and Stulz (1992) and Jorion and Zhang (2007) show that a firm's filing for bankruptcy can have two opposing effects on its rivals: contagion and competition. On one hand, bankruptcy may cause a negative price reaction from rival firms due to contagion. One explanation for contagion is that, due to information cascade and sentiment spillover, the bankruptcy of a firm makes investors and stakeholders of other firms in the same industry worried even about economically sound firms. Another explanation is that the bankruptcy of one firm may reveal negative information about the industry-wide financial and business conditions. On the other hand, a firm's filing for bankruptcy may result in a positive price reaction from rival firms due to redistribution of market shares and profits if the market is not perfectly competitive.

Furthermore, this paper is a part of the growing literature that studies how firms' value and risk are affected by those of their customers and suppliers. A part of the literature (e.g., Acemoglu et al., 2012; Barrot and Sauvagnat, 2016) investigates how sectors and firms affected by temporary disruption impose losses on their customers and how this effect propagates to the entire economy. Another part of the literature analyzes how customers' shocks transmit to suppliers. The suppliers may lose substantial future sales and face difficulties in collecting outstanding receivables if their main customer is exposed to an adverse business shock or becomes financially distressed. Hertzel et al. (2008) and Kolay et al. (2015) find significant negative abnormal stock returns for suppliers following bankruptcy announcements of their major customers. Cohen and Frazzini (2008) and Burt and Hrdlicka (2016) show that customers' returns predict their suppliers' returns. Wu and Birge (2014) find that a firm's return can be predicted by its suppliers' lagged returns, while its customers' lagged returns have less impact.

This paper makes several contributions to the literature. First, past studies of price discovery using interfirm relationships ignore the possibilities of immediate price reactions and are limited to investigating the lead–lag effects between linked firms using low frequency (often monthly) observations (see, e.g., Cohen and Frazzini, 2008; Burt and Hrdlicka, 2016). These studies show that the price discovery process takes at least one month. Our results reveal that information diffuses quickly among linked firms: Return-shock comovement is the strongest contemporaneously and diminishes rapidly.

Different from previous studies, which generally analyze customer–supplier relationships and rival relationships separately, we examine both the linkages in one model. Both our study and Cohen and Frazzini (2008) find that 22% of firm–customer relationships are between firms in the same industry. Additionally, relationships among competing firms may be correlated with the firms' relationships with their customers and suppliers. Therefore, it is essential to disentangle the effects from different types of linked firms by analyzing the linkages in one model.

Moreover, we extend the literature on intra-industry information diffusion. Lang and Stulz (1992) and Jorion and Zhang (2007) show the coexistence of two opposing effects, contagion and competitive, between rival firms around extreme adverse events. Our results about return dependence between rival firms show that contagion and competitive effects are not unique to extreme events; they should also be considered in portfolio choice in normal scenarios. Using the industry concentration rate to measure market competition, we find dependence among rival firms' unexpected stock returns to be positive in a competitive market and negative in a highly concentrated market. This suggests that one of the opposing effects dominates the other depending on market structure. In addition, we find the contagion effect to be stronger in the presence of higher product market fluidity (a measure of the changes in a firm's product market).

Furthermore, we add to the literature on how firms' returns are affected by their customers. Our results show that the degree of dependence on major customers is not the same for all firms; it varies with the firms' characteristics in the product market network. Specifically, we find that the dependence is stronger for firms that rely on their major customer(s) for a greater proportion of revenues and for firms whose products are more similar to the products of rival firms. This finding suggests that large customer concentration and weak product uniqueness lower firms' bargaining power and increase their sensitivity to large customers. Therefore, these are important factors to consider in firms' risk management and investors' portfolio choice.

The remainder of the article is organized as follows. Section 2 presents the data and variables. Section 3 presents our model and estimation strategy. Section 4 describes the results, and Section 5 concludes.

2. Data and variables

In this section, we describe the data and approach we used to identify customer–supplier and rival relationships. Then we show how we form network matrices and calculate firms' characteristics related to the network.

2.1. Customer and rival data

To identify customer-supplier relationships, we use data on US listed firms' major customers from Compustat's Custom Business Unit database. Financial Accounting Standard (FAS) No. 131 in the United States requires firms to provide information about the extent of its reliance on its major customers. In particular, if a customer accounts for 10% or more of a firm's yearly revenues, the firm shall disclose the existence of such customer and the total amount of revenues from each such customer. Firms are not required by FAS No. 131 to disclose the identity of its major customers, but most firms do in practice. The data extend from 1996 to 2014 and consist of the names of major customers and the amount of sales to each of them for each reported firm. In the Custom Business Unit database, the names of major customers can be reported as abbreviations and can vary over time. Inspecting the names, we hand match the reported major customers to the corresponding listed firms reported in the standard Compustat database. We are conservative in the matching to ensure that the right financial information is assigned to customers. We exclude all customers that do not have a match or have ambiguous matches with more than one listed firms. Then, by inspecting the CUSIP identifier of the matched customers, we assign stock returns from the CRSP database to each customer.

To identify rival relationships, we use Hoberg and Phillips's (2010, 2016) 10-K text-based network industry classifications (TNIC) in our main analysis. Previous literature (e.g., Lang and Stulz, 1992; Jorion and Zhang, 2007) has identified firms with the same three-digit standard industrial classification (SIC) code as rivals to each other. In contrast to SIC matching, TNIC matching identifies rival firms based on text-based analysis of firm product descriptions in 10-Ks filed with the Securities and Exchange Commission. By parsing product descriptions, Hoberg and Phillips (2010, 2016) compute continuous measures of product similarity for every pair of US listed firms in each year. For a given firm, *i*, firms having scores of similarity with *i* above a threshold are regarded as rivals to *i*. The likelihood of two randomly drawn firms being rivals to each other is 2.05%, which is the same as the likelihood of two random firms being in the same three-digit SIC code.

TNIC-identified rival relationships have several benefits compared to SIC matching. First, the pairwise product-similarity score is a continuous measure. It can be used to identify which rivals are "nearer" than other rivals. This is particularly informative compared to the SIC-code measure for studying the reaction of one firm's stock return to those of its rivals', as the sensitivity is expected to be higher if similarity is greater. Second, as all the publicly traded firms must file a 10-K every year, so the TNIC changes every year. In contrast, SIC changes much less frequently. Third, TNIC is not a transitive measure of rival relationships. If firm A is a rival to firm B and firm C, B and C may not necessarily compete against each other as their products may not be similar enough. Under SIC matching, however, B and C will be identified as rivals if they both compete against the same firm. As a result, the rival network under SIC contains several closed industry clusters, with an unknown distance between the clusters. Under TNIC matching, in contrast, clusters are connected. We are able to see how firms are connected within and across the clusters.

We collect the TNIC data from Hoberg–Phillips Industry Classification Library. The data report firms that are rivals to a given firm, and their scores of product similarity to it. The data are reported for fiscal years from 1996 to 2013. To check robustness, we also use the SIC to identify rival relationships in the baseline regression analysis. Yearly SIC codes from 1996 to 2013 are collected from Compustat. We identify firms with the same three-digit SIC code as rivals.

2.2. Network

The product network in our study is defined by four network matrices. All the matrices are of order N, with values describing pairwise relationships among the N firms. N indicates the number of firms in the universe in each year and is determined by the number of firms reported in TNIC, since all publicly traded firms must file a 10-K. The first matrix is named the *rival matrix*, $\boldsymbol{W}_t^{\mathrm{R}}$. The values of entries w_{ijt}^{R} and w_{jit}^{R} give the similarity score between firms *i* and *j* if they are rivals in year *t* and are zero otherwise.

The second matrix is the *major-customer matrix*, $\boldsymbol{W}_t^{\mathrm{MC}}$. It describes the relationship between firm *i* and its major customers (if any) in year *t*. The entry w_{ijt}^{MC} is positive if firm *j* is firm *i*'s major customer and is zero otherwise. We expect the link between a firm and its major customer to be stronger when the sales represented by this major customer are larger. Therefore, we equate w_{ijt}^{MC} to the value of sales from firm *i* to firm *j* if firm *j* is firm *i*'s major customer.

The major-customer matrix describes customer–supplier relationships partially. It does not show a firm's relationship with unreported smaller customers. Also, firm *i* may react to some who are not its customers but are in the same industry as its existing customers for two reasons. One reason is that those firms may carry information about the whole customer industry. The other is that those firms may substitute for *i*'s current customers, thus they should be controlled for when we study the relationship between firm *i* and its current customers. Therefore, we develop a matrix that describes a firm's relationship with its small customers and potential customers, the *potential-customer matrix*, $\boldsymbol{W}_t^{\mathrm{PC}}$. We construct the matrix in two steps. First, for a firm that has major customers, the major customers represent the main demand from the downstream side for the firm's products, so we identify the major customers' rival as potential or small customers of the firm in question. Second, for a firm that does not have major customers, we refer to its rivals' major customers (if any) and potential or small customers and regard these firms as the potential or small customers of the firm in question. The key premise for our identification of potential and small customers is that the firms that are rivals have similar products and thus may substitute each other. This is ensured by the TNIC, which is based on product descriptions in firms' 10-K filings. Since the value of sales between a firm and its potential and small customers are not available, we, for simplicity, equate w_{ijt}^{PC} to one if firm *j* is a potential or small customer of firm *i* and to zero otherwise. It should be noted that $\boldsymbol{W}_t^{\mathrm{PC}}$

does not contain relationships between a firm and its major customers, therefore, it does not overlap with $\boldsymbol{W}_t^{\mathrm{MC}}$.[1]

The fourth network matrix is the *supplier-industry matrix*, $\boldsymbol{W}_t^{\mathrm{PS}}$, which describes a firm's relationship with its current and potential suppliers. The construction of this matrix is simple. We first equate $\boldsymbol{W}_t^{\mathrm{PS}}$ to the transpose of $\boldsymbol{W}_t^{\mathrm{PC}}$. Moreover, we equate w_{ijt}^{PS} to one if firm i is a major customer to firm j and to zero otherwise. One should note that the identification of potential suppliers is less precise than the identification of potential customers. Firms that are reported with major customers are not necessarily the major suppliers, so they may not represent significant upstream product suppliers.

As the major customer data and TNIC data change yearly, the network matrices are updated in each year from 1996 to 2013. Annual accounting data such as firms' annual revenue are collected from Compustat for this period. We collect stock returns for the firms that enter the network from mid-1997 to mid-2015 from CRSP. Following the asset pricing literature, we set the lag between accounting data and stock return data to no less than six months. For example, to analyze dependence among stock returns from mid-1997 to mid-1998, we use network matrices in 1996, which are determined based on the TNIC and major customer information in the end of 1996.

Table 1 shows summary statistics for our network linkages. The table shows that, on average, 22% of major-customer linkages are between firms in the same industry. This is

[1] Wu and Birge (2014) use industry supplier returns or customer returns for firms that do not have a supplier or customer recorded in the data. By this approach, they mix the effect of major customers with the customer industry. We account for the possible differences in the effects by separating major and potential customers in two different matrices.

consistent with the percentage documented by Cohen and Frazzini (2008). 28% of potential-customer linkages and potential-supplier linkages are also between firms in the same industry. These indicate the importance of analyzing rival relationships and customer–supplier relationships in one model.

2.3. Characteristics in the network

A main part of this is paper studies the extent to which the effects from other firms are related to firms' characteristics in the product network. Specifically, we examine how industry concentration and product market fluidity affect the spillover between rival firms. These two characteristics indicate the level of competition and product market instability in the industry, respectively. Effects of major customers may be influenced by customer concentration, customer-industry concentration and firms' product uniqueness. As with the data on network matrices, the data on the characteristics are lagged no less than six months compared to stock-return data.

Industry HHI

$Industry\ HHI_{it} = \sum_{j\epsilon\{i'\text{s industry}\}}^{J} \left(\frac{sales_{jt}}{\sum_j sales_{jt}}\right)^2$. This is the Herfindahl–Hirschman index measuring market concentration in firm i's industry in year t. Large industry concentration indicates a low level of competition. Competition is expected to be stronger in industries with greater concentration because companies in these industries may benefit more from rivals' negative shocks. In contrast to the common practice in the literature to calculate *HHI* based on SIC, we calculate the *HHI* based on TNIC. The data for this variable come from Hoberg and Phillips (2010).

Product market fluidity

This variable is developed by Hoberg et al. (2014) using firms' business descriptions in the 10-Ks. It measures the change in a firm's product space due to moves made by competitors (based on TNIC) in the firm's product markets. We expect that when product market fluidity is very high, it is difficult for investors to predict future cash flow of the firms. Therefore, investors may rely more on news about peer firms in the same industry, which induces positive correlation among the stocks of rival firms. The data on product market fluidity data is available from 1997 to 2013. All the estimations where product market fluidity is involved use the return data starting from mid-1998.

Customer-industry HHI

$Cust.HHI_{it} = \sum_{j\epsilon\{\text{industry of } i'\text{s customer}\}}^{J} \left(\frac{sales_{jt}}{\sum_j sales_{jt}}\right)^2$. This is the Herfindahl–Hirschman index measuring market concentration in the industry of i's customers in year t. If a firm's customer-industry concentration is high, it is difficult for the firm to switch customers if existing major customers encounter problems, so this firm is expected to have large exposure to shocks to its major customers. Firm i's customers' industries are identified from the set of i's major and potential customers as defined in Section 2.2. Data on annual sales are taken from Compustat.

Customer concentration

$Cust.Concentr_{it} = \sum_{j\epsilon\{i'\text{s major customers}\}}^{J} \left(\frac{sales_{ijt}}{sales_{it}}\right)^2$, where $sales_{ij}$ represents the sales from i to its major customer j, and $sales_i$ represents the total sales of i. This is a version of Herfindahl–Hirschman index suggested by Patatoukas (2012). It accounts for a firm's major customers and the importance of those major customers for the firm's total revenue. Firms with large customer concentration are more reliant on major customers and thus are expected to have larger exposure to those customers' shocks. The variable takes zero for firms without reported major customers and takes one if a single customer accounts for the supplier firm's entire sales.

Total product similarity

A firm's total product similarity refers to the extent to which the firm's products are similar to those of its rivals. Product similarity has two competing effects on the sensitivity to major customers. On one hand, firms with lower product similarity may have larger bargaining power with their customers, as they face a lower substitution threat from competitors. Therefore, firms with lower product similarity may be less sensitive to adverse shocks to their customers. On the other hand, low product similarity (i.e., high product uniqueness) is usually associated with specialized capital and large expenditures on research and development, which cannot be easily switched to other products in case of reverse demand shocks from major customers. The data on individual firms' product similarity are drawn from Hoberg and Phillips (2010, 2016).

Total product similarity of major customers

In addition, we consider the total product similarity of major customers. The motivation for this variable is analogous to that for the total product similarity of dependent firms. On one hand, if the products of major customers are highly differentiated from those of their competitors, the cost will be high for their supplying firms to switch to other customers, and thus the supplying firms may be more sensitive to the major customers. On the other hand, major customers whose products are unique may be reliant on special input from supplying firms. Thus, the supplying firms may have greater bargaining power during negotiations and lower sensitivity to major customers' shocks. For a firm without reported major customers, the value of this variable is zero. For a firm with major customers, the value is the average of all the major customers' total product similarity weighted by the firm's sales to those major customers.

3. The model and the estimation strategy

Several studies (e.g., Cohen and Frazzini, 2008; Cohen and Lou, 2012) sort firms into quintiles based on linked firms' lagged excess returns and show that the alpha of long–short strategy of extreme quantile portfolios remains positive and persistent up to a year. Burt and Hrdlicka (2016) show that this surprising persistence in alpha—i.e., extreme delay in price discovery—is due to the bias that arises from the linked firms sharing similar misspecification relative to the asset pricing model used. To overcome this bias, they suggest using idiosyncratic shocks—the residuals of a given factor model—to investigate dependence among customers and suppliers. Following the same strategy, we use residuals from Fama and French's (2015) five-factor model as idiosyncratic shocks and examine the cross-autocorrelation between idiosyncratic shocks to linked firms. We start our analysis by estimating a time-series regression model for each asset i.

$$R_{is} = \alpha_{it} + \beta_{it}^{m} R_{ms} + \beta_{it}^{\mathrm{SMB}} SMB_s + \beta_{it}^{\mathrm{HML}} HML_s + \beta_{it}^{\mathrm{RMV}} RMW_s + \beta_{it}^{\mathrm{CMA}} CMA_s + u_{is}$$

$$s = t - S, \dots, t - 1, \tag{1}$$

where R_{is} is firm *i*'s excess return at time *s* and R_{ms}, SMB_s, HML_s, RMW_s, and CMA_s are Fama and French's (2015) factors at time *s*. We estimate the model using the ordinary least square (OLS) method and an estimation window of one year with daily returns. We then use the estimated parameters of this regression model to calculate the out-of-sample idiosyncratic shock of firm *i* in the month following the estimation window:

$$y_{it} = R_{it} - \big(\hat{\alpha}_{it} + \hat{\beta}_{it}^{m} R_{mt} + \hat{\beta}_{it}^{\mathrm{SMB}} SMB_t + \hat{\beta}_{it}^{\mathrm{HML}} HML_t + \hat{\beta}_{it}^{\mathrm{RMV}} RMW_t + \hat{\beta}_{it}^{\mathrm{CMA}} CMA_t\big). \quad (2)$$

Then we move the estimation window ahead by one month to calculate the idiosyncratic shock for the month after the previous out-of-sample window. We repeat this until the idiosyncratic shocks are calculated for December 2015. To focus on the cross-autocorrelation, we use an autoregressive model of order 20 to filter out the autocorrelation in y_{it} before using it in the next step.[2] We use the estimated idiosyncratic shocks, y_{it}, in the following cross-sectional regression model for each day, *t*:

$$\begin{aligned} y_{it} = \mu &+ \rho_t^{\mathrm{R}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{R}} y_{jt} + \rho_t^{\mathrm{MC}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{MC}} y_{jt} + \rho_t^{\mathrm{PC}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{PC}} y_{jt} + \rho_t^{\mathrm{PS}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{PS}} y_{jt} \\ &+ \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{R}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{R}} y_{jt-l} + \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{MC}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{MC}} y_{jt-l} \\ &+ \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{PC}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{PC}} y_{jt-l} + \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{PS}} \sum_{j\neq i}^{N} w_{ijt}^{\mathrm{PS}} y_{jt-l} + \varepsilon_{it}, \end{aligned} \quad (3)$$

[2] We have also estimated the model with unfiltered shocks and the main parameters in the baseline model remain robust.

where w_{ijt}^{R}, w_{ijt}^{MC}, w_{ijt}^{PC} and w_{ijt}^{PS} denote element *i*, *j* of the network matrices for rivals, major and potential customers, and potential suppliers, respectively. Note that all the network matrices are row-standardized, such that for each *i*, $\sum_j W_{ij} = 1$. Using the network matrices as weight matrices, we construct portfolios of the four types of linked firms, respectively. The network matrices are updated yearly, while the return data changes on a daily frequency. Having contemporaneous and $l = 1, \ldots, L$ lagged returns of the portfolios in equation (3), we examine how quickly shock transmits in the network.

$$\boldsymbol{y}_t = \mu + \rho_t^{\mathrm{R}} \boldsymbol{W}_t^{\mathrm{R}} \boldsymbol{y}_t + \rho_t^{\mathrm{MC}} \boldsymbol{W}_t^{\mathrm{MC}} \boldsymbol{y}_t + \rho_t^{\mathrm{PC}} \boldsymbol{W}_t^{\mathrm{PC}} \boldsymbol{y}_t + \rho_t^{\mathrm{PS}} \boldsymbol{W}_t^{\mathrm{PS}} \boldsymbol{y}_t + \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{R}} \boldsymbol{W}_t^{R} \boldsymbol{y}_{t-l}$$

$$+ \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{MC}} \boldsymbol{W}_t^{\mathrm{r}} \boldsymbol{y}_{t-l} + \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{PC}} \boldsymbol{W}_t^{\mathrm{PC}} \boldsymbol{y}_{t-l} + \sum_{l=1}^{L} \lambda_{tl}^{\mathrm{PS}} \boldsymbol{W}_t^{\mathrm{PS}} \boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad (4)$$

where $\boldsymbol{y}_t = [y_{1t}, y_{2t}, \cdots y_{Nt}]'$. *N* stands for the number of firms.

Our model is often labeled the spatial Durbin model (SDM). The SDM specification contains linear combinations of the dependent variable as explanatory variables (i.e., $\boldsymbol{W}_t^{\mathrm{R}} \boldsymbol{y}_t, \boldsymbol{W}_t^{\mathrm{PC}} \boldsymbol{y}_t$, and $\boldsymbol{W}_t^{\mathrm{PS}} \boldsymbol{y}_t$): The returns of competing firms and those of potential suppliers and potential customers to one another enter in the dependent variable and as explanatory variables. This causes an endogeneity problem that may render conventional OLS estimates of the model parameters inconsistent. Maximum likelihood estimation can be used to yield consistent parameter estimates. The log-likelihood function to be maximized at time t is given by

$$\ln \mathrm{L}_t = \ln \left| \boldsymbol{I}_N - \left(\rho_t^{\mathrm{R}} \boldsymbol{W}_t^{\mathrm{R}} + \rho_t^{\mathrm{MC}} \boldsymbol{W}_t^{\mathrm{MC}}{}_t + \rho_t^{\mathrm{PC}} \boldsymbol{W}_t^{\mathrm{PC}} + \rho_t^{\mathrm{PS}} \boldsymbol{W}_t^{\mathrm{PS}} \right) \right| - \frac{N}{2} \ln(2\pi\sigma_t^2) - \frac{\boldsymbol{\varepsilon}_t' \boldsymbol{\varepsilon}_t}{2\sigma_t^2}$$

where σ_t^2 is the error variance that is to be estimated along with the structural model parameters (see, e.g., Anselin, 2006). Given our data, for a firm in each year considered in the LHS of equations (3) and (4), the portfolios $\boldsymbol{W}_t^{\mathrm{R}}\boldsymbol{y}_t, \boldsymbol{W}_t^{\mathrm{PC}}\boldsymbol{y}_t$, and $\boldsymbol{W}_t^{\mathrm{PS}}\boldsymbol{y}_t$ comprise, on average, 61 rivals, 64 potential customers, and 64 potential suppliers. Such large numbers of firms in the portfolios make the endogeneity problem almost negligible. We resort to OLS estimation for our regression due to the computational intensity of searching for a global maximum in the likelihood function. Following Fama and MacBeth (1973), we use the mean and standard deviations of the time-series of the estimated parameters to test for the significance of the parameters.

The model above will be extended by allowing some characteristics to affect the parameters. In this case, the parameters in equation (3) will vary by *i*:

$$\rho_{it}^{\mathrm{X}} = \rho_{t,0}^{\mathrm{X}} + \rho_{t,1}^{X} Z_{it} \tag{5}$$

$$\lambda_{i,tl}^{\mathrm{X}} = \lambda_{tl,0}^{\mathrm{X}} + \lambda_{tl,0}^{\mathrm{X}} Z_{it},$$

where *X* stands for different network matrices and Z_{it} is a network characteristic of firm *i* at time *t*. Accordingly, the model in matrix formation is

$$\begin{aligned}\boldsymbol{y}_t = \mu + \boldsymbol{\rho}_t^{\mathrm{R}}\boldsymbol{W}_t^{\mathrm{R}}\boldsymbol{y}_t + \boldsymbol{\rho}_t^{\mathrm{MC}}\boldsymbol{W}_t^{\mathrm{MC}}\boldsymbol{y}_t + \boldsymbol{\rho}_t^{\mathrm{PC}}\boldsymbol{W}_t^{\mathrm{PC}}\boldsymbol{y}_t + \boldsymbol{\rho}_t^{\mathrm{PS}}\boldsymbol{W}_t^{\mathrm{PS}}\boldsymbol{y}_t + \sum_{l=1}^{L}\boldsymbol{\lambda}_{tl}^{\mathrm{R}}\boldsymbol{W}_t^{R}\boldsymbol{y}_{t-l} \\ + \sum_{l=1}^{L}\boldsymbol{\lambda}_{tl}^{\mathrm{MC}}\boldsymbol{W}_t^{\mathrm{r}}\boldsymbol{y}_{t-l} + \sum_{l=1}^{L}\boldsymbol{\lambda}_{tl}^{\mathrm{PC}}\boldsymbol{W}_t^{\mathrm{PC}}\boldsymbol{y}_{t-l} + \sum_{l=1}^{L}\boldsymbol{\lambda}_{tl}^{\mathrm{PS}}\boldsymbol{W}_t^{\mathrm{PS}}\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t,\end{aligned} \tag{6}$$

where $\boldsymbol{\rho}_t^{\mathrm{X}}$ is an $N \times N$ diagonal matrix with diagonal elements being $[\rho_{1t}^{\mathrm{X}},\ \rho_{2t}^{\mathrm{X}}, \cdots \rho_{Nt}^{\mathrm{X}}]$, and $\boldsymbol{\lambda}_{tl}^{\mathrm{X}}$ is an $N \times N$ diagonal matrix with diagonal elements $[\lambda_{1t}^{\mathrm{X}},\ \lambda_{2t}^{\mathrm{X}}, \cdots \lambda_{Nt}^{\mathrm{X}}]$.

4. Results and analysis

This section consists of three subsections. In the first subsection, we use the baseline model to analyze the contemporaneous and lead-lag relationships among the firms in our defined networks. We also test if firms react differently to negative versus positive shocks to their rivals' and major customers' returns, and if firms' sensitivities are related to their size relative to the firms in their networks. Furthermore, we investigate how our results vary if we use SIC codes instead TNIC to define industries. Finally, we use randomly generated network matrices to examine if the significance of our results is due to the interdependence of the firms in product market networks or are caused by other factors not considered in our model. In the second subsection, we focus on the spillover among rival firms and use several industry characteristics to investigate two opposing effects, the contagion and competitive effects. The third subsection analyzes the spillover from major customers to suppliers. Using several industry characteristics, we investigate factors that may affect firms' sensitivities to their major customers.

4.1. Baseline model

We start with the baseline model presented in equation (3). As return shock, $\boldsymbol{y}_t$, we use residuals from the Fama and French five-factor model according to equations (1) and (2). Since we use daily return shocks, it is important to control for possible autocorrelation in returns. We address this issue in two different ways. The main results are based on idiosyncratic shocks filtered for autocorrelation where we estimate an autoregressive model with 20 lags on the residuals of the five-factor model (equation 2), and filter out the autocorrelation before using the values in the daily cross-sectional regressions in the cross-sectional model (equation 3). Due to the two-stage filtering, this approach may be exposed to the error-in-variable problem. Therefore, we also use an alternative approach: We add 20 lags directly in the cross-sectional model (equation 3). This approach is less exposed to the error-in-variable problem, but assumes that all the autocorrelation parameters are the same for all the firms. The main results are robust to the choice of autocorrelation treatment.

Table 2 shows the estimation results of the baseline model. To save space, we only report the coefficients and mark their significance with asterisks. As expected, the intercept term is very close to zero and insignificant (not reported in the table). The highly significant coefficient for the $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ shows that the contemporaneous effect of shocks is very strong on rivals; 1% idiosyncratic shock affect rivals with 0.1% on average. In order to see if firms react differently to negative versus positive shocks of rivals, we decompose $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ to $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^+$ and $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^-$, where $\boldsymbol{y}_t^+$ and $\boldsymbol{y}_t^-$ are vectors of positive and negative return shocks, respectively, at time *t*. Results (not reported in the tables but are available upon request) show that firms are more sensitive to negative return shocks from their rivals. The coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^-$ is 0.118, while that for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^+$ is 0.087, and both coefficients are statistically significant. The coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^-$ is significantly larger than that for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t^+$ at 1%. It must be noted that return comovement with rivals sums up two opposing effects: a positive effect due to the firms' interdependence from their exposure to common business risks and a negative effect caused by firms competing for market share. In the next section, we decompose rival comovement to these components.

The coefficient for $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ —i.e., 0.035—indicates firms' significant sensitivity to idiosyncratic shocks of their major customers. As with our analysis of the rival effects, we decompose $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ into $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t^+$ and $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t^-$ to see whether firms react differently to negative versus positive shocks to their major customers. The coefficients for $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t^{+}$ and for $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t^{-}$, are 0.043 and 0.032, respectively. Statistically, the former coefficient is larger than the latter at the 10% significance level, indicating that firms are only mildly more sensitive to negative news than to positive news for their major customers. Results for positive versus negative shocks are not reported in the tables but are available upon request.

Interestingly, the coefficient for $\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_t$, which shows the effect of firms in the customers' industries, is also large (0.042) and significant. The significance of this parameter may represent several factors. First, firms may also be sensitive to the economic conditions of their smaller or potential customers. Second, some of the firms included in this group can be important customers without meeting the 10% threshold for their transactions with the supplier firms.

The coefficient for $\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_t$ shows the average effect from supplier industries. This coefficient is highly significant but, as expected, is smaller in magnitude (0.019) than the other parameters, which may reflect a low sensitivity of the firms to their suppliers or may be due to the less precise identification of potential suppliers (as pointed out in Section 2.2).

To investigate if firms respond to shocks to their linked firms with a delay, we use 10 lagged values of the shocks to capture up to a potential two-week delay.[3] Table 2 and Figure 1 show the effects weakening significantly over time. For all the matrices the effect is negligible after one week. In general, the lead–lag effect is stronger between firms with

[3] We have also tried a larger number of lags. Only a very few lags appear to be statistically significant.

rival relationships. The significance of the parameters of the lagged shocks may be related to investors' underreaction and delayed response to shocks or to the cross-autocorrelation resulting from microstructure issues such as nontrading problem of some assets.

The comovement of return shocks displayed in Table 2 may be caused by such factors as inflation and exchange rates not considered in our first-pass regression, rather than by the interdependence of the firms in product market networks. To investigate this possibility, we add a randomly generated network matrix linking the firms with no defined connection. More specifically, for each firm i and for each day t, we randomly select M_{it} firms from the sample of all the firms which are *not included* in the firm's different networks, $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$ and $\boldsymbol{W}^{\mathrm{PS}}$, and construct $\boldsymbol{W}_5$. M_{it} is defined as the average number of firms included in row i of the matrices $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$ and $\boldsymbol{W}^{\mathrm{PS}}$. We use the average number of the linked firms to avoid over- or underestimating the coefficient merely due to the number of links included in $\boldsymbol{W}_5$. We estimate the model with these five network matrices and repeat this procedure 50 times. Table 3 reports the result of the estimation with the maximum absolute value (and absolute t-value) of the coefficient for $\boldsymbol{W}_5\boldsymbol{y}_t$. The coefficient for $\boldsymbol{W}_5$ is very small and negative and the coefficients of $\boldsymbol{W}_5\boldsymbol{y}_{t-l}$ are insignificant for all lags, in almost all 50 random draws. We have also used the maximum number of links in row i of the matrices $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$ and $\boldsymbol{W}^{\mathrm{PS}}$, instead of the average number, as M_{it} and the results hold. The results also remain the same if we use the average number of links in the matrices in general, instead of keeping the average number of links the same for each firm. These findings confirm the relative importance of the network relationships in explaining return covariations.

As discussed above, stock comovements may be due to companies' exposure to some factors or their connections in ways not considered in our setting. If this is the case, then the estimated comovement will be affected by the number of links in the network matrices—i.e., matrices with a larger number of links may give a larger coefficient of comovement. Using randomly generated proximity matrices, Asgharian et al. (2013) show that the estimated value of the correlation coefficient increases with the number of related links. Therefore, we investigate whether the relative importance of our selected networks remains the same if we use the same number of links in each matrix. Since $\boldsymbol{W}^{\mathrm{MC}}$ has the lowest number of links (see Table 1), we reconstruct $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$ for each period by randomly selecting from each of these matrices the same number of links as we have in $\boldsymbol{W}^{\mathrm{MC}}$. Similarly, we also construct $\boldsymbol{W}_5$ for companies without any predefined connections. We repeat the procedure 50 times and reestimate the model. In Figure 2, we plot the minimum and maximum values of the estimated coefficients and the *t*-values from the 50 repeated estimations. Interestingly, it shows that, using the same number of links, the strongest comovement is between suppliers and their major customers. The relative importance of the other network links remains the same. As the minimum *t*-values show, all the estimated parameters, except those related to $\boldsymbol{W}_5$, are statistically significant in all 50 estimations. The parameter related to the major customers is higher relative to the estimation in Table 2, which means that a large part of the comovements between major customers and suppliers were captured by the other linkages among firms. This may to some extent be motivated by the fact that the links in matrix $\boldsymbol{W}^{\mathrm{MC}}$ partially overlap with the links in the other network matrices (see Table 2) and the probability of overlapping should be much lower when we reduce the number of links in those matrices.

Illiquidity of individual stocks can have an impact on the covariance and cross-autocovariance of returns. To examine whether the lead–lag effect shown in Table 2 is not mainly driven by illiquidity, at each estimation day t, we exclude stocks with price under $5 when estimating the baseline model in equation (3). The results remain qualitatively the same. Also, in all the following analyses, the sample that excludes stocks with price under $5 gives results to similar those of the original sample.

Finally, we use SIC instead of TNIC to define $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$. Table 4 shows that using SIC instead of TNIC considerably weakens the coefficient of $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$. This indicates that TNIC captures the similarity of the firms' economic activity better than the conventional SIC classification. We also see a small reduction in the coefficient of $\boldsymbol{W}^{\mathrm{PC}} \cdot \boldsymbol{y}_t$, which gives a similar indication.

4.2. Rival-effect analysis

As shown in Section 4.1, the coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ is relatively large and highly significant, indicating a strong contemporaneous effect of shocks to rival firms. In this section, we aim to further investigate this relationship by decomposing the total impact of rivals into two opposing effects, the so-called contagion and competitive effects. The contagion effect causes a positive interdependence between the firms' values, as rival firms are exposed to similar business risks. The competitive effect, on the other hand, implies a negative comovements between firms' values as rival firms compete for the market share.

The competitive effect should be negligible in a perfectly competitive market, since exit or entrance of an individual firm should not affect the market shares of the other firms in the industry. As industry concentration increases, the number of firms in the industry decreases, we expect the competitive effect to become stronger since an individual firm may substantially benefit from the adverse shocks to its competitor due to the possibility of increasing its own market share. To analyze these effects, we extend the model in equation (3) by allowing the coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t-l}$ to depend on industry concentration (see equation 5). To measure industry concentration, we use the Herfindahl–Hirschman index (HHI) computed using TNIC designations (see Section 2.3). The value of the index is unique for each firm because each firm has a unique set of rivals.

The results are reported in the first set of columns in Table 5. Coefficients for the contemporaneous and lagged terms are allowed to depend on HHI, but, for the sake of space and since the contemporaneous effect being the strongest, we only report and discuss the parameters of the contemporaneous effect. The coefficient for the interaction term between $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ and HHI is negative and statistically significant, supporting our hypothesis that higher industry concentration, by increasing the competitive effect, causes a negative spillover effect among the rivals. That is, a positive (negative) shock to a firm affects its rivals negatively (positively). To estimate the total effect for given levels of HHI, we need to add this negative effect to the positive contagion effect, captured by the coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$. More specifically, as the table shows, the coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ is 0.213, much larger than the corresponding coefficient estimated for the baseline model, 0.105.

The parameter value of 0.213 corresponds to the case when the HHI value is equal to zero and the competitive effect is negligible. The parameter value of 0.105 shows the total affect at the average value of HHI. In Figure 3.A, we depict the marginal spillover effect from rivals (the effect of a one unit change in the contemporaneous return of a rival portfolio) for different HHI values and the related 95% confidence interval. The plot shows that the marginal effect is around 0.21 for the lowest industry concentration level and that it decreases with increasing concentration. When the concentration is around 0.75, the competitive effect offsets the contagion effect, for a net zero effect. For HHI higher than this level, the strong negative competitive effect induces a negative total effect.

Next, we investigate if product market fluidity affects the interdependence of firms in the industry. Greater product market fluidity indicates a more unstable product market. In such a situation, it is difficult for investors to predict firms' future cash flow, and they may, to a greater extent, refer to information about other firms with similar products. We may therefore expect a larger contagion effect among stocks in industries with higher product market fluidity. Similarly to the analysis of industry concentration, we extend the model in equation (3) by defining the coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t-l}$ as a function of firms' product market fluidity (see equation 5).

The second set of columns in Table 5 shows that the coefficient for the interaction term is positive and significant, supporting our hypothesis of a larger interdependence among firm competing in an industry with greater product market fluidity. The coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t}$ is equal to 0.06, much smaller than the corresponding coefficient estimated for the baseline model, 0.105. The parameter value of 0.06 shows the impact of the rival firms in the industry with hypothetically zero product market fluidity, where the contagion effect should be very weak. Greater product market fluidity increases the value of information from other firms and, consequently, the contagion effect (Figure 3.B).

If product market fluidity and HHI were independent, then we could assume that the total effect estimated for different levels of product market fluidity in Figure 3.B would be at the average level of HHI, and similarly the total effects plotted for different level of HHI in Figure 3.A can be assumed to be at the average level of product market fluidity. Since these two variables are not necessarily independent, we estimate a model including both HHI and fluidity. The last set of columns in Table 5 and Figure 3.C show the results. The parameters of the interaction terms are still highly significant, but they become smaller than the corresponding parameter values when using interaction terms separately. The coefficient for $\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ is equal to 0.186, which corresponds to the impact of rival firms when both HHI and fluidity are zero. As Figure 3.C shows, when we increase HHI from zero toward one, the competitive effect increases and reduces the marginal effect, while moving to larger values of fluidity increases the contagion effect and results in a larger marginal effect. The marginal effect is negative for firms with a large concentration ratio (industries with few firms) and low product market fluidity. For these firms, rivals' competitive effect dominates the contagion effect. In general, the contagion effect is stronger than the competitive effect as the total effect is positive for most of the possible combinations of the two variables. Finally, since the figure is plotted using the ranges between minimum and maximum values of HHI and fluidity in our sample, it clearly shows that the marginal rival effects varies more by HHI than by fluidity.

The coefficients of HHI and product market fluidity are both insignificant, indicating that the characteristics themselves do not affect returns; they only affect the sensitivity of the firms to their rivals. The insignificance of the coefficient for HHI does not support the finding of Hou and Robinson (2006) that firms in more concentrated industries earn lower returns.

4.3. Customer-effect analysis

In this section, we turn the focus to the spillover of the shocks in the customer–supplier network, more specifically, from the major customers to the supplier. As discussed before, the coefficient for $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ indicates the average effect that a unit shock to a major customer has on the return of the supplier firm. Using the model in equation (5), we aim to analyze a number of factors that may strengthen or weaken this effect.

We start with the customer-industry concentration, measured by the Herfindahl–Hirschman index. A firm is expected to have a larger exposure to its major customers, if its major customers' industries are less competitive, because it is more difficult for the firm to switch to other customers. Since the interaction parameter in first set of columns in Table 6 is negative and insignificant, our sample does not support this hypothesis. (Note that all the models are estimated with 10 lags to be comparable with the results of the base model, but we only report the parameters of the contemporaneous terms in Table 6.)

Furthermore, we hypothesize that suppliers with a higher customer concentration—i.e., suppliers that depend on a few major customers for a large portion of their sales—should be more sensitive to shocks to their major customers. These firms face risk of losing a large portion of their sale in case of the adverse shocks to their major customers. To measure customer concentration, we use a version of the Herfindahl–Hirschman index suggested by Patatoukas (2012) that captures both the number of major customers and their importance to the supplier firm (see Section 2.3). The coefficient for the interaction term between this measure and $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ is positive and significant, confirming our hypothesis (see the second set of columns in Table 6). Figure 4.A plots the marginal effect of a unit shock to a major customer's return for different levels of customer concentration. The additional effect of a shock to a major customer can vary from 0.029 to approximately 0.10 when the customer concentration increases from zero to one, where a single customer stands for the entire sales of the supplier firm.[4] To see if the firms' sensitivities differs between positive and negative shocks, we decompose $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ **in**to $\boldsymbol{W}^{\mathrm{MC}}\mathbf{y}_t^{+}$ and $\boldsymbol{W}^{\mathrm{MC}}\mathbf{y}_t^{-}$. This shows us how the effects of positive and negative shocks vary with major-customer concentration. The coefficients for $\boldsymbol{W}^{\mathrm{MC}}\mathbf{y}_t^{+}$ and $\boldsymbol{W}^{\mathrm{MC}}\mathbf{y}_t^{-}$ are 0.026 and 0.033, respectively, and both are significant. Interestingly, the coefficient for the interaction term with positive shocks is small (0.061) and insignificant, while the coefficient for the interaction term with negative shocks is 0.129 and statistically significant. This shows that the degree of customer concentration is only important when the major customers experience adverse shocks.

Moreover, we analyze how the uniqueness of firms' product and that of major customers' products and the interdependence between the companies' equity values. We use the total product similarity of individual firms drawn from Hoberg and Phillips (2010, 2016; see Section 2.3). This variable is inversely related to product uniqueness. The third set of columns in Table 6, shows a positive and significant parameter for the interaction term of $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ with firms' product similarity, which supports the hypothesis that firms with unique products have stronger bargaining power against their customers and thus are less sensitive to their customers' shocks. Figure 4.B plots the marginal effect of major customers for different levels of product similarity. The maximum value is around 0.12,

[4] Note that the value 0.035 for the coefficient for $\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ in the base model, reported in Table 2, corresponds to the effect at the average customer concentration.

which is obtained at the maximum value of product similarity in the sample (around 50). As for the uniqueness of major customers' products, we show in the fourth set of columns in Table 6 that it does not affect firms' sensitivity to major customers as the coefficient for the interaction term with major customers' product similarity is insignificant.

Finally, we estimate a combined model with all the characteristics. Results are shown in the last set of columns in Table 6. The estimated parameters are similar to those obtained from separate estimations of different interaction terms, and their significance levels remain unchanged, except that the coefficient for the interaction term with customer concentration becomes significant only at the 5% level.

5. Conclusion

This paper studies how the stock returns of US publicly traded firms are affected by those of the firms competing with similar products and those of the firm's major customers. Using a spatial econometric approach and daily return data, we investigate instantaneous propagation of shocks and testing for a lead–lag effect. Furthermore, we examine how several product market characteristics are related to the extent to which firms are sensitive to the shocks of their rivals and major customers.

We model the contemporaneous and lagged responses of firms' stock returns to the returns of the portfolios comprising, respectively, the firms' rivals, major and potential customers, and potential suppliers in a spatial econometric regression. We find that the returns of all the four types of linked firms affect firms' stock returns. All the effects are the strongest contemporaneously and diminish rapidly thereafter.

We find the effects of rivals and major customers to vary with various characteristics related to the product market network. First, we document the coexistence of contagion and competitive effects among rival firms. Positive (negative) dependence on rivals' returns implies that the contagion (competitive) effect dominates. The competitive effect is found to dominate the contagion effect in highly concentrated industries, while the contagion effect is stronger in industries with higher product market fluidity. Second, the effect of major customers is larger for firms that depend on their major customer(s) for a larger portion of sales and whose products are similar to the products of other firms. This suggests that a concentrated customer base and weak product uniqueness may lower firms' bargaining power and increase the sensitivity of their stock returns to those of their large customers. Furthermore, we show that a firm's stock returns are more sensitive to the negative return shocks than to the positive return shocks of linked firms.

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Table 1. Summary statistics

The table shows the number of firms in the sample and number of pairwise linkages in each network matrix in every year from 1996 to 2013. $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$ denote the network matrices for rivals, major-customer firms, potential customers, and potential suppliers, respectively. The rivalry link from firm *i* to firm *j* is counted separately from the link from *j* to *i*.

		Number of pairwise linkages				Percent of links overlapped with links in $\boldsymbol{W}^{\mathrm{R}}$		
Year	No. of firms	$\boldsymbol{W}^{\mathrm{R}}$	$\boldsymbol{W}^{\mathrm{MC}}$	$\boldsymbol{W}^{\mathrm{PC}}$	$\boldsymbol{W}^{\mathrm{PS}}$	$\boldsymbol{W}^{\mathrm{MC}}$	$\boldsymbol{W}^{\mathrm{PC}}$	$\boldsymbol{W}^{\mathrm{PS}}$
1996	4,464	305,516	1,027	307,861	308,888	19%	27%	27%
1997	4,722	342,560	1,059	298,406	299,465	18%	23%	23%
1998	4,492	293,098	916	223,470	224,386	18%	20%	20%
1999	4,296	295,252	675	238,343	239,018	17%	20%	20%
2000	4,154	303,500	937	263,433	264,370	20%	24%	24%
2001	3,720	243,614	894	235,084	235,978	21%	32%	32%
2002	3,446	213,046	990	257,566	258,556	19%	30%	30%
2003	3,228	184,400	937	233,095	234,032	16%	30%	30%
2004	3,223	185,200	966	190,224	191,190	17%	26%	26%
2005	3,148	179,234	1,005	182,799	183,804	21%	27%	27%
2006	3,134	191,188	1,030	193,953	194,983	24%	26%	26%
2007	3,060	195,570	1,046	224,301	225,347	26%	30%	30%
2008	2,900	163,250	1,003	163,779	164,782	24%	31%	31%
2009	2,793	138,396	1,090	148,899	149,989	25%	24%	24%
2010	2,721	138,626	1,029	170,705	171,734	26%	34%	34%
2011	2,648	145,094	992	195,534	196,526	29%	32%	32%
2012	2,534	129,290	972	177,608	178,580	26%	33%	33%
2013	2,575	151,390	981	190,186	191,167	27%	37%	37%
Mean	3,403	211,012	975	216,403	217,378	22%	28%	28%

Table 2. Baseline model with 10 lags

The table presents the results for the baseline model in equation (3). $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$ denote the network matrices for rivals, major and potential customers, and potential suppliers, respectively. Stock returns are on a daily frequency from mid-1997 to mid-2015 from CRSP. The network matrices are updated yearly from 1996 to 2013. The parameters marked with one asterisk are significant at the 5% level, and those with two asterisks are significant at the 1% level.

	$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_{t\text{-}l}$
Lag 0	0.105**	0.035**	0.042**	0.019**
Lag 1	0.018**	0.011**	0.012**	0.005**
Lag 2	0.009**	0.001	0.010**	0.003**
Lag 3	0.007**	0.000	0.006**	0.001
Lag 4	0.004**	0.003	0.004	0.003**
Lag 5	0.005**	0.005*	0.001	0.001
Lag 6	0.003**	0.001	0.003	0.001
Lag 7	0.002*	0.005*	0.004	0.001
Lag 8	0.004**	0.000	0.003	−0.002
Lag 9	0.004**	0.002	0.000	0.001
Lag 10	0.002	0.005*	0.001	0.001

Table 3. Baseline model with an additional random *W* with no defined connection

The table presents the results of an augmented baseline model in equation (3), where we add the matrix, $\boldsymbol{W}_5$. $\boldsymbol{W}_5$ is a randomly generated network matrix, in which, M_{it} linked firms that are not linked in row i of the matrices $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$ are assigned to firm i at time t. M_{it} is defined as the average number of firms included in row i of the matrices $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{MC}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$. We repeat this procedure 50 times. This table reports the result with the maximum absolute value (and absolute t-value) of the coefficient for $\boldsymbol{W}_5 \cdot \boldsymbol{y}_t$. The parameters marked with one asterisk are significant at the 5% level, and those with two asterisks are significant at the 1% level.

	$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_{t\text{-}l}$	$\boldsymbol{W}_5\boldsymbol{y}_{t\text{-}l}$
Lag 0	0.104**	0.037**	0.040**	0.019**	−0.007**
Lag 1	0.018**	0.011**	0.013**	0.005**	0.001
Lag 2	0.009**	0.000	0.010**	0.003**	−0.002
Lag 3	0.008**	0.000	0.006*	0.001	0.000
Lag 4	0.005**	0.003	0.004	0.003*	0.000
Lag 5	0.005**	0.005*	0.001	0.001	−0.001
Lag 6	0.004**	0.001	0.003	0.001	−0.001
Lag 7	0.003*	0.003	0.004	0.001	0.001
Lag 8	0.005**	−0.001	0.002	−0.002	0.000
Lag 9	0.004**	0.003	0.001	0.001	0.000
Lag 10	0.002	0.005**	0.001	0.001	0.001

Table 4. Baseline model with 10 lags using SIC for rival-relationship identification

The table shows the results for the baseline model (3) when SIC is used to identify rival relationships and define $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{PC}}$, and $\boldsymbol{W}^{\mathrm{PS}}$. The parameters marked with one asterisk are significant at the 5% level, and those with two asterisks are significant at the 1% level.

	$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_{t-l}$	$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_{t-l}$	$\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_{t-l}$	$\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_{t-l}$
Lag 0	0.026**	0.045**	0.032**	0.020**
Lag 1	0.017**	0.013**	0.014**	0.006**
Lag 2	0.009**	0.003	0.009**	0.005**
Lag 3	0.004*	0.001	0.004*	0.004*
Lag 4	0.004*	0.003	0.004*	0.001
Lag 5	0.004*	0.004*	0.003	0.000
Lag 6	0.004*	0.001	0.003	−0.001
Lag 7	0.001	0.002	0.006**	−0.003
Lag 8	0.003	0.000	0.002	0.000
Lag 9	0.001	0.002	0.000	0.003
Lag 10	0.003	0.005**	−0.002	0.001

Table 5. The impact of product market characteristics on rival effect

The table shows the results for the baseline model (3) with extension (5), where the coefficient for the portfolio of rivals depends on Herfindahl–Hirschman index and product market fluidity. The parameters marked with one asterisk are significant at the 5% level, and those with two asterisks are significant at the 1% level.

	Industry HHI		Product Market Fluidity		All	
	β	*SE*	*β*	*SE*	*B*	*SE*
Intercept ×100	0.001	*0.0035*	0.007	*0.0058*	0.005	*0.0057*
$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$	0.213**	*0.0026*	0.060**	*0.0028*	0.186**	*0.0038*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$	0.032**	*0.0023*	0.034**	*0.0024*	0.032**	*0.0024*
$\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_t$	0.021**	*0.0024*	0.020**	*0.0026*	0.006**	*0.0025*
$\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_t$	0.010**	*0.0012*	0.011**	*0.0013*	0.005**	*0.0013*
$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ × Industry HHI	−0.285**	*0.0050*			−0.256**	*0.0052*
$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$ × Fluidity			0.007**	*0.0014*	0.003*	*0.0005*
Industry HHI ×100	0.003	*0.0100*			0.004	*0.0107*
Fluidity ×100			0.000	*0.0007*	0.000	*0.0007*

Table 6. The impact of product market characteristics on major customer effect

The table shows the results for the baseline model (3) with extension (5), where the coefficient for the portfolio of major customers depends on the Herfindahl–Hirschman index of the customer's industry, customer concentration, total product similarity, and total product similarity of major customers. The parameters marked with one asterisk are significant at the 5% level, and those with two asterisks are significant at the 1% level.

	Customer HHI		Customer Concentration		Similarity		Customer Similarity		All	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Intercept ×100	0.002	*0.0040*	0.003	*0.0037*	0.002	*0.0040*	0.004	*0.0038*	0.001	*0.0044*
$\boldsymbol{W}^{\mathrm{R}}\boldsymbol{y}_t$	0.104**	*0.0014*	0.106**	*0.0014*	0.101**	*0.0014*	0.104**	*0.0014*	0.100**	*0.0014*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$	0.039**	*0.0039*	0.029**	*0.0028*	0.024**	*0.0030*	0.030**	*0.0037*	0.022**	*0.0075*
$\boldsymbol{W}^{\mathrm{PC}}\boldsymbol{y}_t$	0.038**	*0.0025*	0.041**	*0.0025*	0.032**	*0.0025*	0.040**	*0.0025*	0.026**	*0.0025*
$\boldsymbol{W}^{\mathrm{PS}}\boldsymbol{y}_t$	0.018**	*0.0012*	0.019**	*0.0013*	0.016**	*0.0012*	0.018**	*0.0012*	0.016**	*0.0013*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ × Cust. HHI	−0.018	*0.0145*							0.002	*0.0179*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ × Cust. Concentr.			0.078**	*0.0217*					0.057*	*0.0240*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ × Similarity					0.002**	*0.0005*			0.003**	*0.0008*
$\boldsymbol{W}^{\mathrm{MC}}\boldsymbol{y}_t$ × Cust. Similarity							0.000	*0.0009*	−0.001	*0.0013*
Cust. HHI ×100	0.007	*0.0082*							0.007	*0.0084*
Cust. Concentr. ×100			−0.025	*0.0255*					−0.028	*0.0299*
Similarity ×100					0.000	*0.0004*			0.000	*0.0004*
Cust. Similarity ×100							−0.001	*0.0010*	−0.001	*0.0012*

Figure 1. Delay in responding to the shocks to linked firms.

The figure shows the *t*-values of the coefficients for the contemporaneous and one- to 10-day lags of the portfolios of the four types of linked firms.

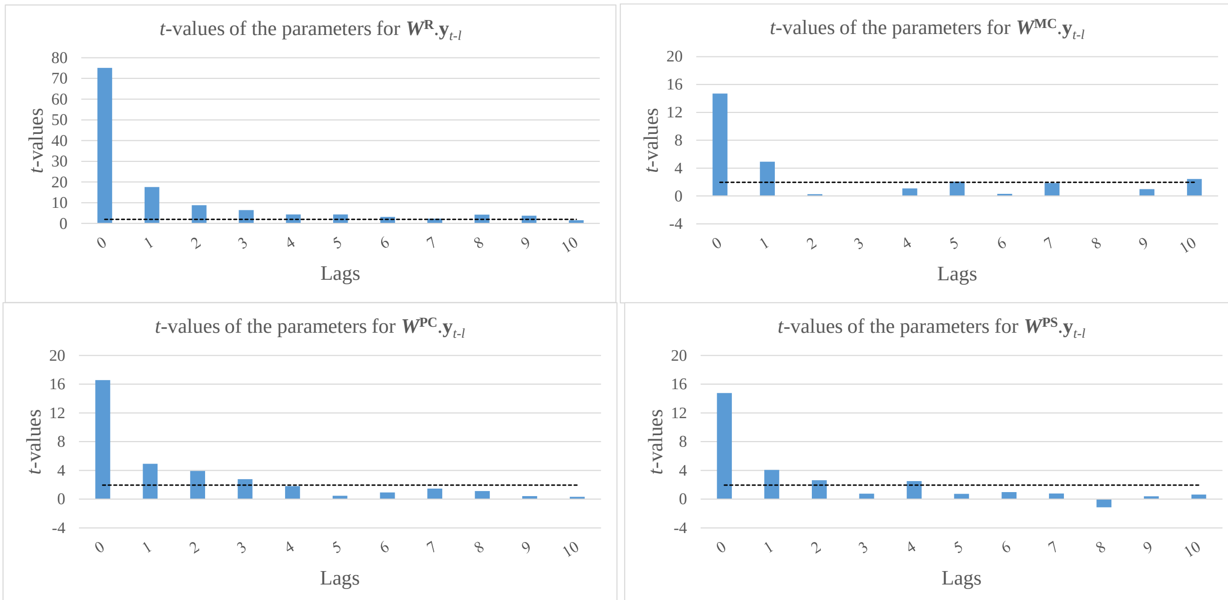

Figure 2. Augmented baseline model with the same number of linkages

The figure shows the minimum and maximum values of the estimated coefficients and the t-values from 50 repeated estimations using the same number of links in all the matrices. We reconstruct $\boldsymbol{W}^{\mathrm{R}}$, $\boldsymbol{W}^{\mathrm{PC}}$, $\boldsymbol{W}^{\mathrm{PS}}$, and $\boldsymbol{W}_5$ for each period by randomly selecting from each of these matrices the same number of links as we have in $\boldsymbol{W}^{\mathrm{MC}}$.

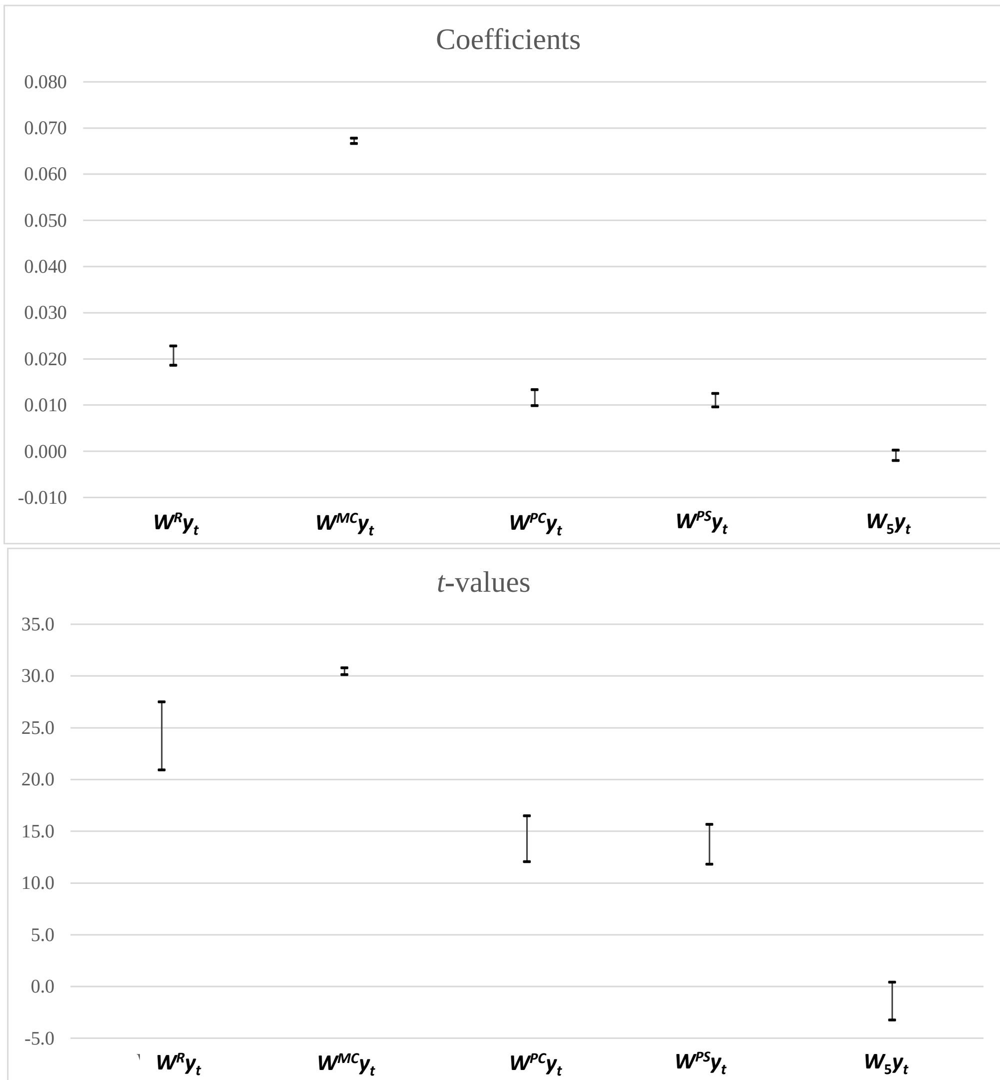

Figure 3. The variation of the rival effect with product-market characteristics

The figure shows the effect of a unit change in the contemporaneous return of a portfolio of rivals varying with HHI and product market fluidity, using estimates from Table 5. Figures A and B show the marginal rival effects for different levels of the two characteristics, separately, and the associated 95% confidence intervals. Figure C shows the marginal rival effect when both characteristics change.

Figure 3.A

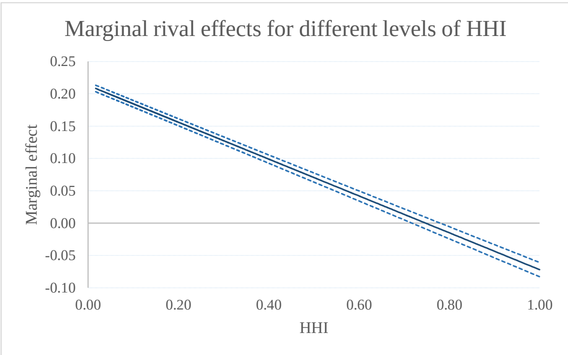

Figure 3.B

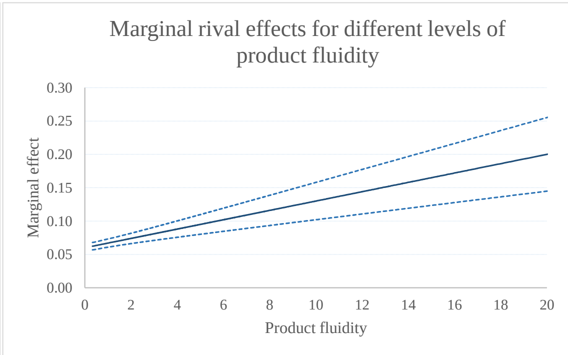

Figure 3.C

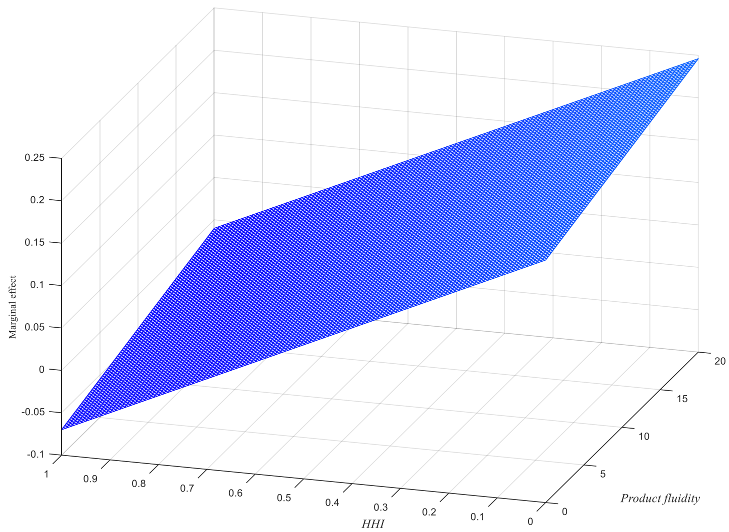

Figure 4. The variation of major-customer effect with product market characteristics

The figure shows the effect of a unit change in the contemporaneous return of a portfolio of firms' major customers for different levels of customer concentration (A) and total product similarity (B), using estimates from Table 6. The figure also shows the associated 95% confidence intervals.

Figure 4.A

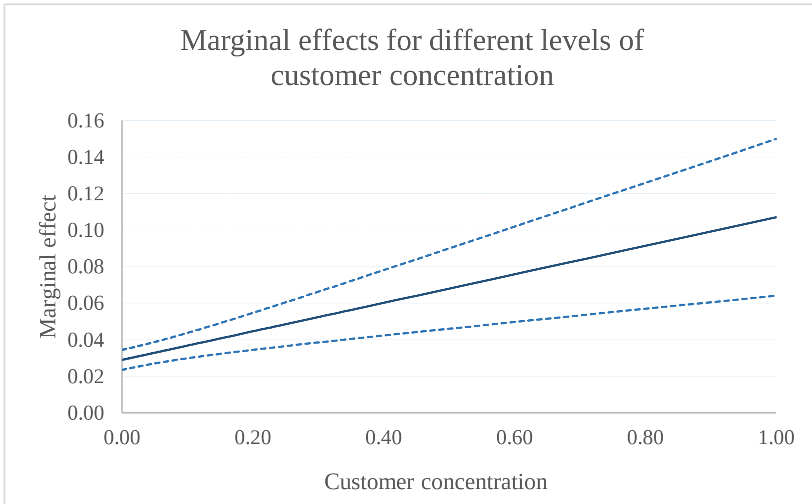

Figure 4.B