THE UNIVERSITY OF CHICAGO

FIRM PERFORMANCE AND RISK IN SUPPLY CHAIN NETWORKS

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE UNIVERSITY OF CHICAGO
BOOTH SCHOOL OF BUSINESS
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
JING WU

CHICAGO, ILLINOIS
JUNE 2016

To my parents: Jianying Li and Qiyong Wu

The more I learn, the more I realize how little I know.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I am foremost grateful to John R. Birge for his guidance and constant support during my graduate life. It has been a real privilege to work with John and I have learned a lot from his enthusiasm on research and immense knowledge. His spirit of dedication and humbleness as a genius scholar will inspire me to never cease on thinking and learning. I am thankful to Christopher S. Tang for his valuable encouragement, insightful advices, and the philosophy on research. During our collaboration on a research project, Chris has been extremely generous with his time, which he has little to spare. I will cherish my interactions with him.

My sincere thanks goes to other members of my committee, Elena Belavina, Rene Caldentey, and Bryan T. Kelly, for their valuable time, perspectives and comments in improving this work. Elena reminded me to collect different feedbacks. Rene helped me better position my research. Bryan supported me on the empirical data and methodology. I am indebted to S. Alex Yang, who has helped me tremendously in the past six years since he introduced me to the graduate study. I am also indebted to Dan Adelman, Volodymyr O. Babich, Lauren H. Cohen, Eugene F. Fama, Vishal Gaur, N. Bora Keskin, and Alireza Tahbaz-Salehi, who encourage me and provide feedbacks at different stages of this work.

I would like to acknowledge the financial support from the Booth School of Business and Fama-Miller Center for Research in Finance. I appreciate the internship with Deutsche Bank New York, where Yin Luo's Equity Quantitative Strategy Team contributed great ideas from the practitioner's point of view, and supported me generously on the research data.

I thank my fellow doctoral students for all their help, especially: Thomas Best, Jung Ho Choi, Nitish Kumar, Brett Lombardi, Angelo Mancini, Antonio Picca, Matthew Stern, Jianyu Wang (UCLA), Weichen Wang (Princeton), Yongning Wang, Xiaolong Wu, Qiao Xiao, Jin Zhang, Yu Zhang (Princeton), Frank Zhou. Finally, I thank my parents for giving me the opportunity to learn and grow. I know they would be proud of my graduation.

ABSTRACT

Firms do not exist in isolation but are linked to each other through supply chain relationships. The complexity and opacity of the network of interconnections among firms inhibit understanding of the impact of management decisions concerning the boundaries of the firm and its relationships with others. My dissertation proposes to answer the following questions regarding firm performance and risks in supply chain networks.

First (Chapter 1), how do a firm's suppliers and customers affect its performance? How does a firm-level shock propagate in the supply chain network? By leveraging recently available data on supply chain relationships, my results show that supplier and customer returns explain firm performance as reflected in stock returns, which are also predicted by supplier-lagged returns. I also show credit shock propagation in the supply chain network.

Second(Chapter 2), how do the network position and the number of connections to a firm affect its risk? For the effects from multiple connections, I find that the network centrality measures have different risk implications for firms operated in different industries. Specifically, more central firms in the manufacturing (logistics) industry have lower (higher) risk. Further, I develop a theoretical model to explain systematic risk derived from the supply chain network structure and the correlation of firm-level shocks.

Third (Chapter 3), facing many partners in the supply chain network, does buyer direct financing outperform an outside financial intermediary? Using a three-party game theoretical model, I show that when possessing proprietary information, the manufacturer only has an edge in offering financing directly if the supplier has extremely low asset value. This simplifies supply chain network analysis as the issues for financing, which should be mostly offered by outside financial intermediaries, can be separated under an optimal configuration.

CHAPTER 1

FIRM PERFORMANCE IN SUPPLY CHAIN NETWORKS

1.1 Introduction

Firms do not exist in isolation but are linked to each other through supply chain relationships. The firms and their supply chain relationships compose the supply chain network, in which the links transmit idiosyncratic shocks [1], such as changes in a firm's individual performance expectations. Assessing the relative costs and benefits of adding, deleting, and absorbing supply chain connections naturally gives rise to many questions such as the following that we pose in categories as first-order and second-order effects respectively. First, from the shock transmission perspective, since shocks may be transmitted at different speeds and at different intensities, what are the effects of these shock transmissions and how do upstream and downstream transmissions differ? This is the question I explore in Chapter 1. Second, from the risk management perspective, since the idiosyncratic shocks transmitted along the supply chain network may depend on each other, do firms strategically choose a supply chain network structure to mitigate risk and how does this effect depend on the firms' industry and market positions? This question is discussed in Chapter 2.

Previous literature has studied the first question both at the industry level and at the firm level. At the industry level, for example, Menzly and Ozbas (2010) find strong own lagged effect and both upstream and downstream cross-prediction effects across industries using BEA (the U.S. Bureau of Economic Analysis) input-output data; Shahrur et al. (2010) extend that methodology to international trade. Using recent observations, Fruin et al. (2012) study different time horizons for trailing cross-industry lagged effects and find that longer-term (more than three-month) frequency signals are not statistically significant. While industry relationships may affect an individual firm, they also reflect within-industry lag

1. "Idiosyncratic shocks" in this paper means firm-level shocks, which may be correlated across firms depending on the business characteristics such as industry sector and geographic location.

effects in which large firm returns generally lead those of smaller firms (see, e.g., Menzly and Ozbas (2010)), possibly masking the impact of a firm's direct relationships. For literature at the firm level, Hendricks and Singhal (2003) find evidence that firm returns decrease at the announcements of supply chain glitches, particularly production or shipment delays. In addition, Cohen and Frazzini (2008) find evidence of return predictability in the supply chain, providing a test of investors' attention constraints, while Kelly et al. (2013) build a model of upstream shock transmission for firm level volatility and find that size dispersion and volatility dispersion move together. At a more refined level of analysis, Atalay et al. (2011) examine firms' ownership of production chains and find no clear evidence for intra-firm trade (suggesting different reasons for vertical integration). To the best of our knowledge, our results are significantly different from the previous studies as we are the first to examine the differences between supplier firm shock and customer firm shock transmission, for both the intensity and the speed. We also show a structural diffusion mechanism at the firm level compared to the industry level result by Menzly and Ozbas (2010).

To address the question of relative upstream and downstream impact, we develop a theoretical framework in which shocks propagate through the supply chain in both directions, with possible contemporaneous and lead-lag effects. Using cross-sectional supply chain data, we construct a relationship-weighted map quantifying firm-level supply chain structure within the U.S. economy. We first test for the customer lagged effect documented by Cohen and Frazzini (2008) using recent data and find that the customer lagged effect is no longer significant. Interestingly, we still observe significant own lagged effect and supplier lagged effect. We also find that a supplier lagged effect trading strategy yields significant abnormal excess returns in back-testing. We further investigate the return information diffusion for firms operating in different industries according to the first two digits of the North American Industry Classification System (NAICS) standard, which define the large industry sectors[2],

2. On the one hand, we wish to use fine-grained industry classifications so that firms in unrelated lines of business are not grouped together. On the other hand, using too fine an industry classification results in

and find that the supplier lagged effect exists in most industries.

We study the shock transmission as reflected in firm returns information for two principle reasons. First, firm return data has higher frequency than operational measures such as revenues and profit that are generally only reported quarterly. The frequency of trades of a firm's shares provides us with a sufficient number of samples in the chosen horizon to conduct tests of relationship impact. Second, firm return data endogenizes operations information and thus gives cleaner information on the expectation and the riskiness of firm earnings than real economic measures. Since stock returns reflect information updating, the lagged effect between supplier and customer firms is a joint test of both investor inattention to supplier chain information and the real effect of supply chain shock transmission delay. To consider alternative mechanisms for the lag effect we observe, in robustness tests, we control for common asset pricing factors and rule out alternative explanations as reported in previous literature, including institutional holding, trading volume, analyst coverage, and market capitalization.

The rest of the chapter is structured as follows. Section 2 introduces the theoretical model and hypotheses for the first-order effect from direct connections. Section 3 describes the supply chain data set we use in this study. Particularly, we introduce a data set from a major financial data company, which captures much richer cross-sectional information than the commonly known Compustat segment data. Section 4 examines the empirical test results. We show that a firm's return can be explained by its one-month supplier lagged returns. Section 5 summarizes the findings and suggests other directions such as event study on credit shock propagation.

---

portfolios that are statistically unreliable. Choosing first two-digit classifications strikes a balance between these two concerns.

1.2 Model of Firm Performance in Supply Chain Network

In this section, we propose a model in which the supply chain network transmits firm return shocks through direct firm connections both contemporaneously and with a one-month lag. With this model, we can then investigate the speed and the intensity of shock transmission for both upstream and downstream directions and formulate hypotheses on the relative importance of supplier influence versus customer influence for the current period and the one-month forward period.

For this network model, we suppose that firms compose the nodes of the network and that their sales relationships form directed links. We let sales determine the link strength, which is similar to what is proposed by Menzly and Ozbas (2010), in which the relationship weight is computed using the flow from one industry sector to another, and in Kelly et al. (2013) for relative firm influence on growth. This relationship is intuitive since firms are likely to be affected more if a major supplier or customer experiences a shock than if the shock comes from a minor supplier or customer. For the annual sales from firm i to firm j, we use $sales_{ij}$, which is then an output from firm i and input to firm j and will be weighted by the total sales of firm i as an output and by the total sales of firm j as an input. In this model, we assume that the supply chain relationships are sufficiently stable for a short period of time. Particularly, for our empirical tests, we assume that the supply chain structure is predetermined and exogenous to stock returns for the monthly window from July 2011 to June 2013, a total of 24 time series observations, and that this information should also be accessible to investors ex ante.

We let w_{ij}^{in} denote the input supplier weight for j as a fraction of i's procurement and let w_{ij}^{out} denote the output customer weight for j as a fraction of i's sales:

$$w_{ij}^{in} = \frac{sales_{ji}}{Total\ Procurement_i} = \frac{sales_{ji}}{\sum_{k=1}^{N} sales_{ki}}, w_{ij}^{out} = \frac{sales_{ij}}{Total\ Sales_i} = \frac{sales_{ij}}{\sum_{k=1}^{N} sales_{ik}}.$$

We propose that these weights relate to the propagation of return shocks through the network with common damping parameters $\beta_k, k = 1, \ldots, 5$, which correspond to the rate of propagation from own lagged effect (one-period lagged own returns), supplier lagged effect (one-period lagged weighted output returns), customer lagged effect (one-period lagged weighted input returns), concurrent supplier weighted returns, and concurrent customer weighted returns. We then define $r_{i,t}$ as the return of firm i in month t, which is a linear combination of its own one-month lagged effect, weighted sum of supplier and customer one-month lagged effect, weighted sum of supplier and customer returns, as well as its own idiosyncratic shocks:

$$r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 \sum_j w_{ij}^{in} r_{j,t-1} + \beta_3 \sum_j w_{ij}^{out} r_{j,t-1} + \beta_4 \sum_j w_{ij}^{in} r_{j,t} + \beta_5 \sum_j w_{ij}^{out} r_{j,t} + \epsilon_{i,t}. \tag{1.1}$$

The coefficients α and β_k, $k = 1, \ldots, 5$ are then to be estimated; $\sum_j w_{ij}^{in} r_{j,t-1}$ is the one-month supplier lagged effect, $\sum_j w_{ij}^{out} r_{j,t-1}$ is the one-month customer lagged effect, $\sum_j w_{ij}^{in} r_{j,t}$ is the concurrent supplier return, and $\sum_j w_{ij}^{out} r_{j,t}$ is the concurrent customer returns. This model is in accordance with the valuation model in (1), since it explains the relative changes in expected dividends as a result of expected cash flow shocks to customers and suppliers. The lag effects represent delays in the diffusion of these expectations . In our empirical tests by both pooled OLS and Fama-MacBeth, we also introduce common risk factors into (2) to examine the independent effects of the relationships.

From the above definition, both the in-degree weights and the out-degree weights are normalized such that $\sum_j w_{ij}^{in} = \sum_j w_{ij}^{out} = 1$ and $w_{ii}^{in} = w_{ii}^{out} = 0$. For firms that do not have a supplier or customer recorded in our data, we use industry supplier returns or customer returns to avoid possible singularity in the ordinary least square estimation. The industry returns are value-weighted by other firms in the same industry according to the full NAICS code classification.

From basic operations theory, firm cash flows depend on reliable inputs from suppliers and orders from customers. We, therefore, expect to find strong positive relationships between firm performance expectations, hence, contemporaneous stock returns and those of suppliers and customers. Independent changes in stochastic discount factors should also affect firms and their supply chain partners in the same directions.

Theory for the presence of a lagged effect is less consistent. The form of lagged effect we consider here is serial autocorrelation (as opposed to consistent relative performance of winners versus losers as in the common definition of a momentum factor). For individual firms, some rational theories predict positive serial correlation (e.g., Johnson (2002)), while others predict negative serial correlation (e.g., Berk et al. (1999)). Sagi and Seasholes (2007) also provide a firm model that allows for either positive or negative serial correlation depending on the firm's growth prospects and costs of operation. Behavioral theories generally support positive autocorrelation (under-reaction, e.g., Barberis et al. (1998)) or negative autocorrelation (overreaction, e.g., Bondt and Thaler (1985)). Empirical findings generally indicate short-term (and longer term over one year) negative autocorrelation (e.g., Fama and French (1988)) and intermediate term positive autocorrelation (e.g., Jegadeesh (1990), Jegadeesh and Titman (1993)). Portfolios of firms sorted by size (Brennan et al. (1993)) and industry groups (Moskowitz and Grinblatt (1999)) also exhibit short-term positive autocorrelations. In addition, other issues, such as trading inactivity, can create autocorrelation.

Our focus here is on the relationships among firms, which makes direct predictions about lagged effects even more ambiguous. For example, positive one-month autocorrelation across industry groups may imply observed positive serial correlation with suppliers (who may serve the entire industry) but negative one-month serial autocorrelation for individual firm returns may imply negative one-month serial correlation for suppliers without a diversified customer base.

If investors pay limited attention to supply chain relationships, both supplier and customer lagged effects can be supported by operations management theory. When a supplier receives an idiosyncratic shock, its customer firms may be affected by the supplier's disruption due to the delivery lead time and the friction in switching suppliers. Such supply disruptions have significant and lasting impacts on the customer's share price as Hendricks and Singhal (2003) show in event studies. Effects may also appear first with suppliers if buyers observe private signals of future prospects and pass on these expectations to suppliers in the form of new contract terms or order quantities which change cash flows of the supplier before the buyer. If investors pay limited attention to such events or information about the relationship is slowly diffused, then we may observe a lag in the shock effect from the supplier to the customer.

A possible example of this form of supplier lagged effect appears in the aftermath of the Philips semiconductor fabrication plant fire in March 2000 (Latour (2001)). While the severity of the disruption was not immediately known, potential market reaction appeared in the price of Philips's shares (PHG), which dropped 13% in value in March 2000. The stock of Ericsson (ERIC), a major customer of Philips which relied on this plant for cell phone chips, was only down slightly (2%) in March 2000 but then declined by 6% in April and 7% in May 2000 (and steadily for the next several years), indicating a possible lagged effect from the supplier disruption. Another Philips customer supplied by this plant, Nokia (NOK), had a much different experience, rising 12% in March 2000 and another 1% in each of April and May 2000. In contrast to Ericsson, Nokia also had alternative suppliers (who may in fact have benefited from the Philips disruption) and did not experience a significant production disruption. In this case, Nokia appears to have benefited from the second-order interaction effect of having multiple supplier relationships. We explore this effect in more detail in the next chapter.

In addition to the supplier disruption effect, when a customer firm receives an idiosyncratic shock, its supplier firms may be affected by the customer lagged effect due to a change in future production orders. Cohen and Frazzini (2008) give an example of Callaway Golf Corporation and Coastcast, a manufacturer of golf club heads, in which Callaway's price dropped significantly in June 2001 while Coastcast's dropped proportionally in July 2001. While Cohen and Frazzini (2008) found a significant customer lagged effect, their exposure of this return relationship and associated trading strategy may have motivated investors to pay greater attention to these supply chain relationships and to eliminate this effect. Potential evidence of increased awareness include news media (e.g., Boesler (2013)), which have started to cover the customer lagged effect strategy. Moreover, investment banks have published white papers on the past performance of the customer lagged effect (e.g., Salvini et al. (2012), Cahan et al. (2013)) and have developed relevant research products on their trading platforms (e.g., Balch (2013)). Even if investors corrected the inefficiency regarding customer relationships revealed in 10Q filings as used in Cohen and Frazzini (2008), we still would not know whether investors have recognized all customer information. We may or may not, therefore, observe a significant customer lagged effect in our tests using more complete supply chain information. Therefore, we consider the possibility that underreaction or investor inattention may persist or that the publication of these results may have alerted investors sufficiently to devote greater attention to customer connections[3].

Overall, we hypothesize significant supplier and customer effects for current period returns but have alternative hypotheses of positive or insignificant customer effects. We do, however, hypothesize that it is still possible to observe returns predictability using supplier lagged returns since that effect may be less salient to investors.

Hypothesis 1. *Concurrent supplier and customer returns explain a firm's returns.*

3. According to proprietary information from some anonymous hedge fund managers, customer lagged effect has been fully exploited after the appearance of Cohen and Frazzini 2008.

Hypothesis 2. *Supplier lagged returns predict a firm's returns significantly.*

Hypothesis 3. *(A) Customer lagged returns predict a firm's returns significantly. (B) Customer lagged returns do not significantly predict a firm's returns.*

1.3 Data

A major difficulty in studying supply chain networks is the observability of the network. For tractability, we limit our attention to the supply chain network formed by publicly listed firms in the U.S. Therefore, we omit private firms, the foreign sector, government, and household consumption from our consideration. Public firms disclose supply chain data in a variety of ways, including but not limited to public filings, conference call transcripts, capital markets presentations, sell-side conferences, firm press releases, product catalogs, and firm websites. Some information is disclosed mandatorily, while other is disclosed voluntarily due to value-maximizing managers' incentive to accommodate the capital markets, as shown, for example, in **?**.

Mandatory supply chain disclosure requirements among public firms vary globally. In the United States, under the Securities and Exchange Commission's (SEC's) Statement of Financial Accounting Standards No. 14 (SFAS 14), "if 10% or more of the revenue of an enterprise is derived from sales to any single customer, that fact and the amount of revenue from each such customer shall be disclosed" in interim financial reports issued to shareholders (including annual and other quarterly reports). The segment part of the Compustat database, which has about 30 years of time-series records, captures this information. In addition, some non-major customers, which compose less than the 10% threshold of a firm's sales, are also voluntarily disclosed in public filings and thus captured by Compustat.

In recent years, financial data firms such as Bloomberg and Standard & Poor's have endeavored to fill in the missing relationships beyond the public filings. The Bloomberg Supply Chain Data (SPLC) function, available on the Bloomberg terminal application, provides the business relationships between many firms in terms of the flow of sales. More than half of the relationships in Bloomberg SPLC are not, however, quantified (with only the existence of a directed link, i.e., the names of the supplier firm and the customer firm, indicated), but other firm pairs include an estimate of sales based on one (or more) of the possible public sources. We do not use the unquantified relationships in this paper (leaving that for future research). For the quantified relationships with actual sales amounts, Bloomberg computes the relationship percentage between firms on both a customer (revenue) and supplier (cost) basis. Bloomberg SPLC uses a variety of sources, including the public filings, for the quantified relationships. The reliability of the data set is documented in that every quantity captured is backed up by a source, which is accessible on the Bloomberg terminal.

Bloomberg keeps track of about 26,000 public firms worldwide in their universe, among which about 4,500 are US firms. Of this number, a total of 2,152 U.S. firms in SPLC have quantified supply chain data. This reduction in coverage from all public firms to those with quantified relationships underscores the difficulty in collecting supply chain information, even after investigating other sources beyond the public filings.

Since Bloomberg SPLC also uses public filings, the Compustat segment data is a subset of SPLC, which we validate by data merging. The public filings represented in the Compustat segment only contribute to fewer than 10% of the relationships in the Bloomberg SPLC data, as most quantified relationships are created by Bloomberg's estimates. According to Bloomberg documentation available on its terminal (SPLC<GO>), to create supply chain estimates, Bloomberg first constructs an exhaustive list of customers and suppliers to a firm based on disclosures found in all sources. Analysts then review the company's business model to understand how the individual segments are tied into its customers and/or suppliers, then break the revenue stream (as disclosed in company filings) down to its most granular level and match customers/suppliers to specific revenue or product streams where the relationship most likely resides. For example, the analyst would typically connect a semiconductor manufacturer with the personal computer segment of an electronics manufacturing firm.

The advantage of Bloomberg SPLC is that it captures richer cross-sectional information than public filing data alone. Unfortunately, Bloomberg SPLC is, however, only a cross-sectional data set with the latest annual relationships; so it does not offer archival data as in the Compustat segment. This is mainly due to the fact that estimates of historical sales are both arduous and difficult. Due to the time series data limitation, we use a two year sample period by assuming the supply chain network remains unchanged. Since our data have richer cross sectional information, we have a more detailed model specification than previous literature[4]. Since SPLC is a newly created product and Bloomberg updates the information on firms in its universe frequently, including supply chain news, we may, however, anticipate time series data in the future.

We merge the 2012 cross-sectional data from Bloomberg SPLC and the Compustat segment, both as of June 2, 2013. Since the Bloomberg terminal is designed mainly for practitioners, the natural identifier for firms is the ticker symbol. The ticker symbol, however, tends to change frequently over time and to have duplicates; hence, we first automatically merged the dataset using both ticker and CUSIP and then hand-matched those if at least one of the identifiers did not match. As expected, Bloomberg SPLC captures the relationships in Compustat but with some newer updates using the estimates. For such situations, we average the values from both data sets and delete the duplicate relationship. We note that Bloomberg SPLC includes a few customer relationships above the 10% threshold that do not appear in the Compustat data, suggesting that it is possible that firms may conceal major customers in public filings to mitigate the costs of aiding competitors as discussed in **?**.

After data cleaning, 11,819 U.S. domestic relationships are left, of which 865 are from public filings and 10,954 from Bloomberg estimates. This set then provides richer cross-

4. In unreported tables we replicate our findings at 12-month (July 2012 to June 2013), 18-month (Jan 2012 to June 2013) and 30-month (April 2011 to September 2013) windows. The results are qualitatively identical, showing the robustness of our assumption on the stable supply chain relationships.

sectional information than the Compustat segment data, which only captures an average of 1,124 relationships per year in the past 30 years according to Cohen and Frazzini (2008). Since the majority of the data is based on the Bloomberg database, we use SPLC to refer to our merged supply chain network data.

Even though our data is downloaded contemporaneously, actual report dates for both public filings and proprietary estimates vary due to different reporting and estimation dates. Figure 1.1 shows the distribution of SPLC's report dates. The earliest report date for our data set is April 3, 2012, while the latest report date is June 2, 2013. The median report date is Feb. 19, 2013 while 52.9% of the report dates concentrate in the first four months of 2013. Since supply chain relationships are sufficiently stable over short horizons, we assume the cross-sectional data set reflects supply chain network structure for the monthly window from July 2011 to June 2013, a total of 24 time series observations. We downloaded the monthly firm returns from the Center for Research in Security Prices (CRSP) within that window, which covers three exchange platforms in the U.S. market, NYSE, AMEX and NASDAQ, and 99.72% of the firms in the SPLC. The 6 tickers missing in CRSP for the selected period do not affect our results since they are missing, either due to recent listings (DXM and ENVS) or delistings due to bankruptcy or otherwise very low stock prices (CRCV, FOHL, PCXCQ and VLTC), and might have undesired liquidity effects if included.

Since our data does not capture the complete supply chain network, it is important to understand any systematic biases. Using the closing market value on the last day of 2012, we compare the coverage of our data to the CRSP universe in terms of firm size distribution. The log-size distribution is shown in Figure 1.2. We use red for firms in CRSP and blue on top of the red for the SPLC firms. Both the SPLC data and CRSP universe seem to have approximately lognormal size distributions. The firm size distribution of SPLC is, however, clearly biased towards larger firms, which intuitively makes sense. This suggests that the supply chain relationships involving large firms are easier to capture than those involving

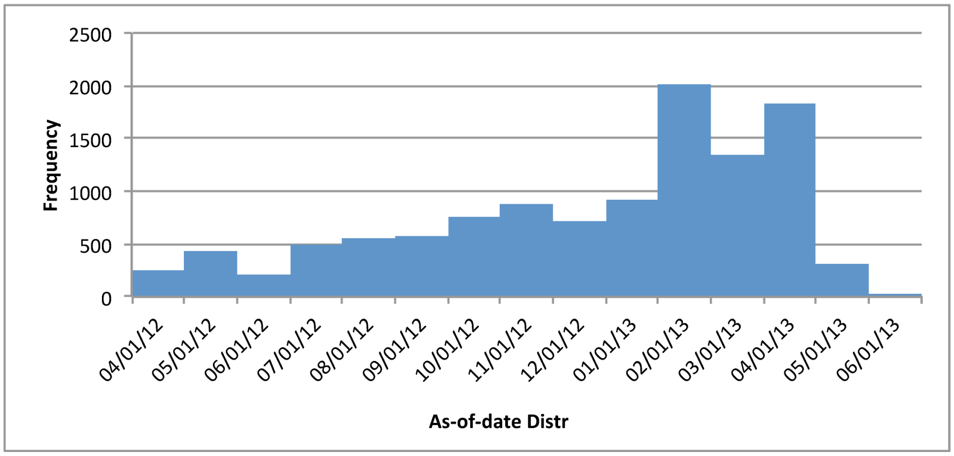


Figure 1.1: Sales Report As-of-date Distribution

only small firms. Firms, especially small ones, also have incentive to not disclose, or even hide their supply chain relationships for competition concerns, as discussed in **?**. Given this observation, we would anticipate that small firms would exhibit more bias from intentional concealment or voluntary disclosure than large firms and that SPLC's greater large firm representation reduces this bias.

Supplier relationships may also have different importance for firms in different industries. A car manufacturer relies on its supply chain partners heavily to produce cars just-in-time, while a bank may still be able to operate properly if the ordered office laptops are delayed. Therefore, it is important to see the coverage bias in terms of industry breakdown. In Figure 1.3, we plot the total firms captured in our data according to the first digit of the NAICS code and compare these numbers to the total firms in CRSP. We use blue to indicate the number of firms in our data and red to indicate the the number of firms not captured. The first bar represents industries starting with Code 2, including mining, utilities, and construction, of which we can see that 197 out of 402 firms in this large sector are captured by SPLC, a coverage ratio of approximately 50%. The second bar represents industries starting with Code 3, i.e., manufacturing, and the third bar represents industries starting with Code 4, i.e. the logistics sector which includes wholesale, retail, warehousing, and transportation. Our

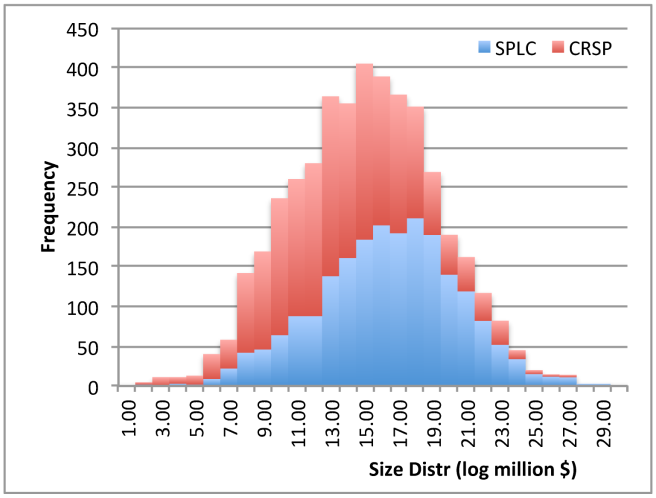


Figure 1.2: Firm Log-size Distribution

data have about 65% coverage for both manufacturing and logistics. This coverage ratio is consistent even if we further break down these categories using the first two digits of the NAICS code. The fourth bar represents industries starting with Code 5, i.e., various service industries. While overall coverage in this grand service sector is almost one quarter, the coverage ratios vary dramatically within groups selected. For example, the fifth bar shows that our data only covers 3.4% of firms in finance and insurance (NAICS 52), compared to coverage of 94.6% of firms in professional, science, and technology (NAICS 54) as shown in the last bar. Overall, the manufacturing and logistics sectors have the most consistent cross-sectional firm coverage in our data.

We further investigate the distributions of the captured relationships. Figure 1.4 shows the histograms of in-degree and out-degree per firm, which seem to follow a power law distribution. Characterizing the exact degree distribution is beyond the scope of this paper, but we note that other research, such as that of Atalay et al. (2011), argues that the power law distribution may over-predict the number of minimally connected firms. It is also worth mentioning that not all firms have both supplier and customer relationships captured in our data; 670 firms do not have supplier information, while 587 firms do not have customer

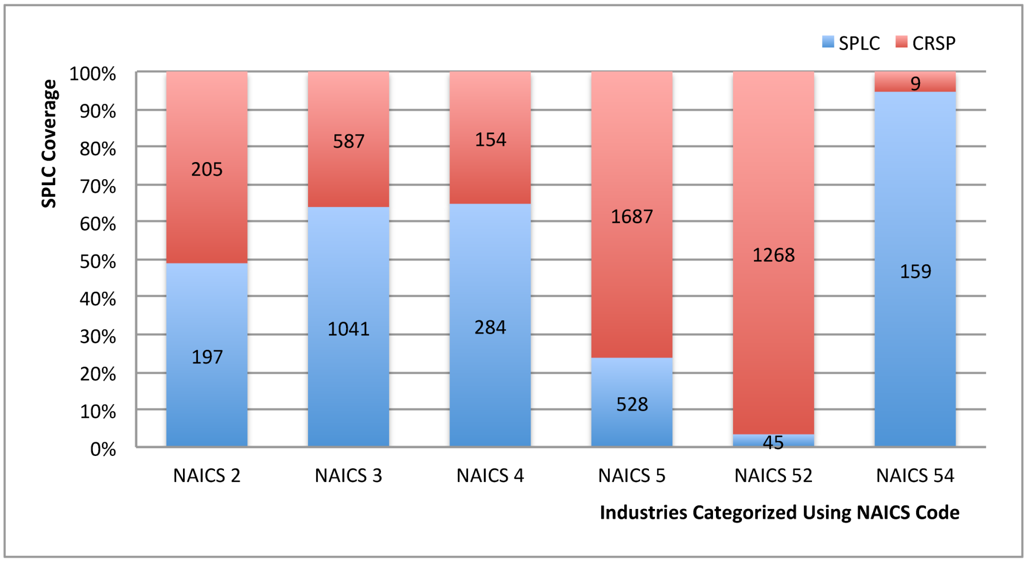


Figure 1.3: Firm Coverage of Industry Breakdown

information. We need special treatment for these firms, as discussed in the next section.

Since the Compustat dataset captures sales that are more than 10% of suppliers' revenue, we consider the extent of the sales below the 10% threshold in our data. Figure 1.5 shows the distribution of sales contribution percentages, which are the ratios of captured sales quantity to the total revenue made by the supplier firm. The left figure shows the distribution of the 865 relationships above the 10% threshold; the right figure shows that of the 10,954 relationships below the 10% mark. We note that the sales contribution here also seems to follow a power law distribution.

Table 1.1 shows summary statistics of our data. In Panel A, we report firm coverage. Among the 2,152 firms in our dataset, 1,576 firms function as suppliers to other firms, while 1,496 firms function as customers to other firms. The total market capitalization of the firms in our dataset is about 14.2 trillion dollars. For comparison to the CRSP universe, CRSP has 5,090 firms in our chosen time window and a total market capitalization of about 19.3 trillion dollars according to 2012 annual fundamentals. Thus, our dataset covers 42.3% of the total number of publicly listed firms in the U.S. market and 75.0% of the total market

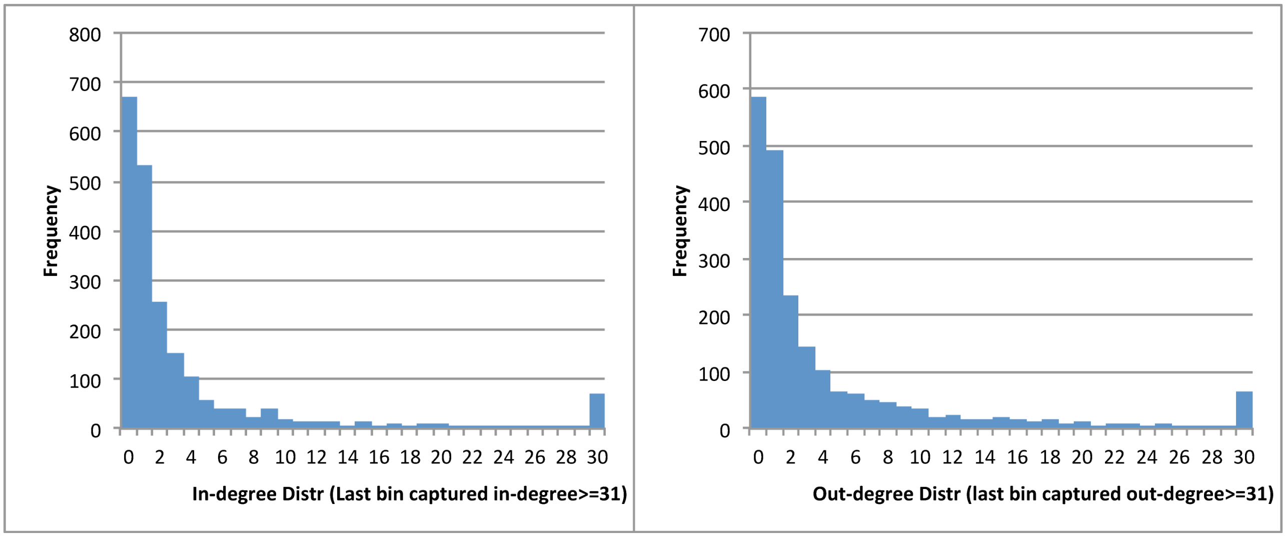


Figure 1.4: In-degree and Out-degree Distribution

Notes. The last bars in both distributions represent the number of firms that have no less than 30 in-degree (or out-degree) relationships. Descriptors of the data in this figure, mean, median, and power law coefficients, are given in Table 1. For reference, firms with large degree are listed in Table 2 as "Top 10 most connected firms."

capitalization. The fact that SPLC has a larger coverage over the market cap than the number of firms indicates again that SPLC is tilted toward large cap firms, which can also be seen from the mean and median firm sizes. The average firm size in SPLC is 6,740 million dollars, compared to the average size in CRSP of 4,447 million dollars. The median in SPLC is 1,112 million dollars, compared to the median in CRSP of 550 million dollars. Overall, we conclude that SPLC covers a significant portion of public firms in the U.S. economy.

In Panel B we report summary statistics on the link information. The mean of supplier / customer per firm is 5.16, while the median is only 1, indicating a sparse network in general, in which, many firms are actually on supply chain paths instead of networks. We estimate the degree distribution using the maximum likelihood method described in Clauset et al. (2009), and find coefficients of 1.88 for out-degree customer and 2.76 for in-degree supplier; therefore, the out-degree customer distribution has a heavier tail than the in-degree supplier distribution. Since smaller sales relationships are more likely to be missing compared to

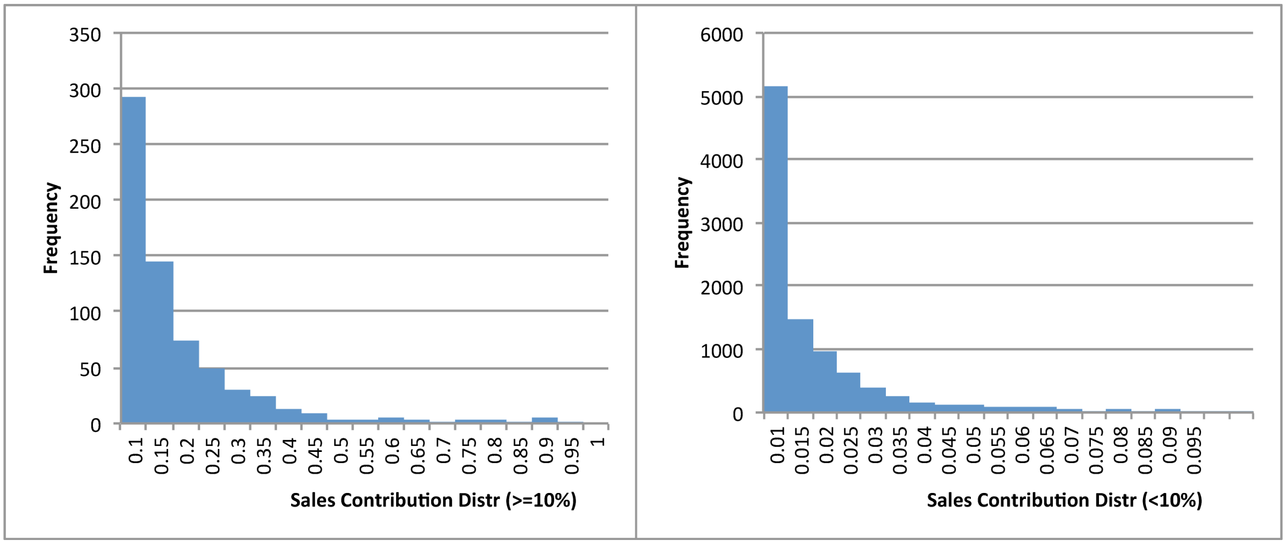


Figure 1.5: Sales Contribution Distribution

Notes. This figure shows the sales contribution of all relationships captured in our data. The sales contribution is the ratio of captured sales quantity to the total revenue of the supplier firm.

larger sales, the true degree distributions should have even heavier tails and our coefficient estimates should be overestimated relative to the actual power law coefficients.

For every firm, we also compute the ratio of the total captured sales to total revenue. We find on average, a firm only has 16.09% of its total sales identified in our data. If we use revenue-weighted averages and consider the whole economy, we find an even lower ratio of 11.01%. This means that in aggregate, a large portion of sales relationships are still missing, which has an implication for the centrality measure we use in the next section. Overall, we believe that our data may compute a relatively realistic order in terms of a first-order centrality measure for firms, such as eigenvector centrality and degree centrality, but may be biased for higher order centrality measures such as supplier concentration or customer concentration.

We argue that a significant part of missing sales are due to the omission of private firms, household consumers, and government, as well as foreign sectors, which may be significant suppliers or customers for many firms as in the examples below.

1. Lockheed Martin Corporation has 9.67 billion dollars in sales to the public sector, i.e., the U.S. government, which is 82.0% of its 2012 annual revenue.

2. Intel Corporation sold 1.41 billion dollars, 11% of Intel's 2012 annual revenue, to Lenovo Group Ltd., a Chinese firm and the 2nd largest personal computer manufacturer in the world.

3. Best Buy Company purchased 1.33 billion dollars, 10.41% of Best Buy's COGS in 2012, from Samsung Electronics, a Korean firm.

4. Cargill, a privately held firm, had 133.9 billion dollars in sales in 2012. Its customer base includes retail giants such as Wal-Mart and Target, although the exact quantities in these relationships are unknown.

Overall, we conclude that the firms covered in the SPLC account for a major part of the U.S. economy. The basic distribution patterns discussed suggest the measures of supply chain network captured by our data are meaningful. Since our main interest is to observe the effects of firm centrality and systematic risk, we believe that missing end-customer nodes, such as government and household consumers, and less-connected segments, such as foreign sectors, would have relatively little influence on risk propagation. We also believe that the omission of private firms, few of which would appear among the largest firms in the most heavily covered NAICS segments, also introduces little bias to the measured centrality-risk relationships.

To further show the economic network in the data, we plot the cross-sectional supply chain network of the 2,152 firms in Figure 1.6 using a force-directed layout algorithm proposed in Fruchterman and Reingold (1991). In this algorithm, spring-like attractive forces based on Hooke's law are used to attract pairs of endpoints of the graph's edges towards each other, while simultaneously repulsive forces like those of electrically charged particles based on Coulomb's law are used to separate all pairs of nodes. In equilibrium states for this system, the edges tend to have uniform length, and nodes that are not connected by an edge tend

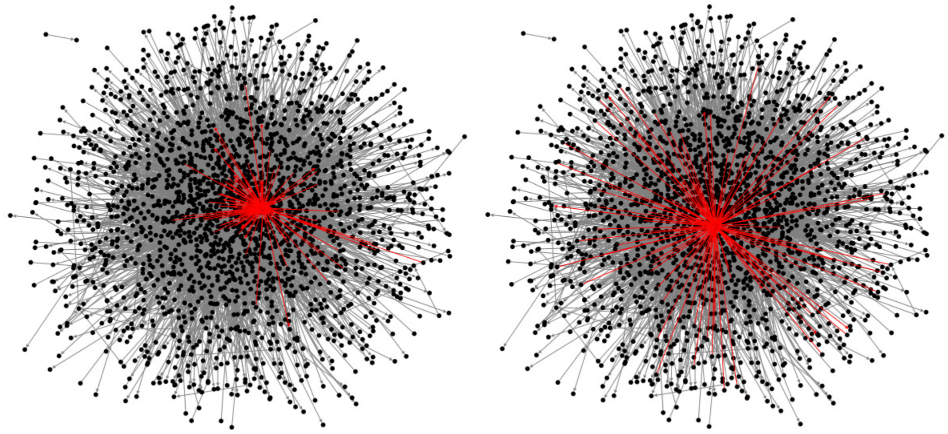


Figure 1.6: Supply Chain Network Captured by SPLC (Left: Apple, Right: CVS).

Notes. These diagrams depict the Bloomberg SPLC dataset as of June 2, 2013 using the Fruchterman-Reingold layout algorithm. In equilibrium states for this system, the edges tend to have uniform length; nodes that are not connected by an edge tend to be drawn further apart. Apple's links are colored red on the left, while CVS's links are colored red on the right.

to be drawn further apart. As a result, well-connected nodes tend to be placed in more central positions while less-connected nodes are placed at the periphery. This is useful to show companies with different positions in the supply chain network.

We consider two firms, Apple and CVS, which are both highlighted in red in Figure 1.6. Apple has a total of 135 relationships (30 out-degrees, 105 in-degrees, which ranks 11 in terms of total degree in the dataset) while CVS has a total of 127 relationships (10 out-degrees, 117 in-degrees, which ranks 12 in terms of total degree) captured by SPLC. Since both firms have many links in our data, the nodes representing Apple and CVS both tend to be placed near the center of the network. However, CVS connects to more peripheral firms than Apple, which can be seen from the length of the links. As a result, Apple has a eigenvector centrality of 6.784×10^{-3}, much higher than CVS's eigenvector centrality of 2.028×10^{-3}.

Table 1.2 shows the 10 most connected firms in the SPLC data. Wal-Mart is the most connected public firm in the US economy, but it does not have a single customer firm captured in our data since it sells primarily to household consumers. IBM is the second most connected firm in the US economy and is the fourth most connected firm in terms of both in-degree and out-degree. This level of centrality for IBM stems from its position in supplying business information solutions, which require inputs from upstream semiconductor and device firms, and sales to various business customers. For example, IBM's top US supplier is Intel Corporation, which sold 242.9 million dollars of goods to IBM in 2012, including Intel's Xeon® CPU, a major input for IBM's business server products, which are then sold to many downstream business customers such as the US Postal Service, Verizon Communications, and AT&T Inc.

We can also observe from Table 1.2 that most of the top connected firms belong to manufacturing (NAICS code 31-33) and the logistics (NAICS code 42-49) industries. The degree data availability for those two large industry sectors agrees with the industry coverage result as shown in Figure 4.

1.4 Empirical Results

We first run a pooled OLS regression of the network model of returns for the full panel data, using variants of the regression (1). Our primary interest is the explanatory or predictive power of $\sum_j w_{ij}^{in} r_{j,t-1}$, $\sum_j w_{ij}^{out} r_{j,t-1}$, $\sum_j w_{ij}^{in} r_{j,t}$ and $\sum_j w_{ij}^{out} r_{j,t}$. To be considered in the following tests, a firm must meet a minimum liquidity threshold of \$5 share price in the chosen horizon. This ensures that portfolio returns are not driven by micro-capitalization effects for illiquid securities. This also helps to avoid delisting (which generally occurs when stock prices fall below one dollar) and infrequent trading issues that can lead to stale pricing effects such as inflated serial correlation.

Table 1.3 summarizes the results. Observing each column, we see that the effects of the concurrent supplier and customer returns are significant for both univariate and multivariate regressions, supporting Hypothesis 1. In the first row, the concurrent supplier returns have a coefficient of 0.370, close to the concurrent customer returns coefficient of 0.387. In the univariate cases, the coefficients are respectively 0.517 and 0.587. The magnitudes of these coefficients show that our data provide economically meaningful supplier chain relationships.

We next investigate lagged effects, i.e., one-month lagged responses to own, supplier, and customer shocks. For all cases, the one-month own lagged effect is significant with slightly negative coefficients, meaning high past own returns predict low future own returns. As we noted above, this effect also appears in Fama and French (1988), Jegadeesh (1990), and other studies without the presence of supplier and customer returns terms. For the cross-firm lagged effect, we find that in all cases the supplier lagged effect is statistically significant, but that the customer lagged effect is not significant. This supports Hypothesis 2 and 3(B). The supplier lagged effect has a statistically significant coefficient of 0.025 when current-period connections are also included. Comparing the first row with the second row, the supplier lagged effect has a higher coefficient of 0.044 when we omit the contemporaneous effects. The rows with at least one concurrent variable all have an adjusted R^2 greater than 13%, while the cases with no concurrent variable have an adjusted R^2 less than 0.2%. This shows that variations in the dependent variable are mostly explained by concurrent cross-firm returns.

Overall, the panel data regression results suggest that both customers and suppliers have significant concurrent effects, of which the first is slightly stronger than the second, but only suppliers have a significant one-month lagged effect. The cross-lagged effect results have two important implications for the time window we choose. First, from the financial market perspective, investors may be subject to limited attention to suppliers as opposed to customers. Another reason could be that firms are more reluctant to disclose supplier information than their customer information; thus, supplier information is more difficult to obtain for investors. Second, from an operations management perspective, the gradual diffusion of information in the downstream direction may indicate lack of downstream supply chain coordination, i.e., supplier firms withholding proprietary operational news from downstream firms. The asymmetric information may be attributed to different market power that upstream players and downstream players possess in the supply chains. Another possible reason for the gradual downstream information diffusion is that customer firms may order less, foreseeing a demand shock; thus, supplier firms would show a decrease in sales before the customer firms due to the delivery lead time. Overall, the cross-lagged effect results can be explained by a combination of supply chain operations and investors' insufficient perception of supplier information.

We construct similar tests with different horizons, finding that the significance drops as the horizon increases, with the 2-month trailing returns coefficients being significantly weaker than the one month signal, and the 3-month trailing returns coefficients being insignificant. In the following we focus on one month lagged returns to avoid biasing the t-tests with overlapping forward periods.

1.4.1 Fama-MacBeth Regression

Pooled OLS results may be biased since the residuals may not be independently and identically distributed. Since the residuals of a given year may be correlated across firms, we use Fama-MacBeth regression as in Fama and MacBeth (1973) to deal with the time effect. As discussed in Petersen (2009), the Fama-MacBeth method estimates the loadings on risk factors in two steps to avoid problems of correlation across contemporaneous residuals in panel data. The first step runs T cross sectional regressions to obtain estimated coefficients for assets while the second step uses the coefficient estimates to find the loading estimates. A detailed discussion of the Fama-MacBeth method is provided in the Appendix. We also assume the correlation of firm residuals in different years is weak and proceed with the Fama-MacBeth regression as follows[5].

Each month in our time window has its own set of monthly regression coefficients. We calculate the average coefficient for each signal across months and then calculate the t-

5. The average firm return auto-correlation is -0.020, and the average firm return residual auto-correlation is -0.011.

statistic to test whether each coefficient is statistically different from 0. The results are shown in Table 1.4.

Similar to Table 1.3, in both the univariate and multivariate cases, the coefficients for concurrent supplier and customer returns and the supplier lagged effect are significant, but the coefficients for the customer lagged effect are not significant. Own momentum is significant with slightly negative coefficients, again consistent in all cases. Comparing Table 1.4 to Table 1.3, the concurrent customer has a much larger impact than the concurrent supplier. In the first row, the downstream coefficient of 0.755 is almost twice as large as the upstream coefficient of 0.399. Our results then suggest that investors should pay more attention to a firm's customers than to its suppliers for the contemporaneous effect but should mainly care about its suppliers for cross-firm lead-lag effects.

1.4.2 Robustness Test

To further explore the robustness of our results, we want to see whether we still observe the same results after controlling for the common factors of market premium, size, value, and momentum. We add these common factors to form the following regression (2):

$$
\begin{aligned}
r_{i,t} \;=\; & \alpha + \beta_1 r_{i,t-1} + \beta_2 \sum_j w_{ij}^{in} r_{j,t-1} + \beta_3 \sum_j w_{ij}^{out} r_{j,t-1} + \beta_4 \sum_j w_{ij}^{in} r_{j,t} + \beta_5 \sum_j w_{ij}^{out} r_{j,t} \\
& + b_i \left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + u_i MOM_t + \epsilon_{it}, \qquad (1.2)
\end{aligned}
$$

where SMB stands for "Small (market capitalization) Minus Big", HML stands for "High (book-to-market ratio) Minus Low", and MOM stands for "Momentum" of average returns on the two high prior returns portfolios minus the average returns on the two low prior return portfolios. Those factors measure the stock's exposure to small caps over big caps, value stocks over growth stocks, and winner stocks over loser stocks. All the factors are defined by self-financing portfolios. The factor data is readily available from the Kenneth French data library[6].

Table B.1 summarizes the results[7]. We see similar qualitative results to those in Tables 3 and 4, i.e., both current suppliers and customers explain a firm's return, while customers are more important than suppliers for the current period effect; for the lagged effects, both the supplier one-month lagged effect and the own lagged effect are significant. The customer lagged effect is only slightly significant for the univariate case. Comparing the columns of Table 5 to the corresponding columns of Table 4, the coefficients for concurrent supplier and customer returns are smaller. The weaker sensitivities for current cross-firm returns are due to the fact that some concurrent cross-firm effects are explained by the common factors.

Since Menzly and Ozbas (2010) find strong upstream and downstream industry effects, we further examine whether the supplier and customer firm effects are different from the upstream and downstream industry effects. After replacing the firm returns on the right hand side of the regression (1) by the industry returns that the firm resides in based on the first 3 digits of the NAICS codes, we observe smaller coefficients and the respective t-stats of the cross-sectional regression in an unreported table, while the signs are the same. The adjusted R-square also reduces significantly by 6.2% to 12.8% compared to that in Table 3. This robustness check indicates that the supplier and customer firm effects explain returns better than the supplier and customer industry effects. We also find positive own lagged effect for the 1-month returns as in Moskowitz and Grinblatt (1999).

Although results such as the supplier lagged effect are consistent with the investor's limited attention hypothesis, there are a number of other plausible explanations of the data. We next present results for a series of robustness tests for investor inattention.

A number of papers find that larger firms, or firms with higher levels of analyst coverage,

6. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

7. A complete table with loadings on the common factors is in Appendix.

institutional ownership, and trading volume, lead smaller firms or firms with lower levels of analyst coverage, institutional ownership, and trading volume (e.g., Lo and MacKinlay (1990), Brennan et al. (1993), Badrinath et al. (1995), Chordia and Swaminathan (2000), Hou and Moskowitz (2005), Hou (2006)). The supplier lag effect results could be caused by firms of different size, analyst coverage, institutional ownership, and trading volume. To ensure that our results are not driven by those alternative explanations, we conduct the following robustness tests by constructing filters. For checking the firm size effect for example, we only pick the firms that have their market capitalization larger than the input supplier weighted firms' market capitalization. In other words, the firms we pick are all larger firms compared to their average supplier firms weighted by their purchase orders. Since smaller supplier firms are less noticeable to investors, then, if we still see a significant supplier lagged effect, this should not be due to larger sizes of upstream firms. We apply similar filters using levels of analyst coverage, institutional ownership, and trading volume. A detailed description of the alternative explanation robustness tests is provided in the Appendix. A brief result is given in Table 1.6. The supplier lagged effect is still significant after different filters, which means those possible alternative explanations cannot alone explain the supplier lagged effect. Different from Menzly and Ozbas (2010), we find negligible changes after removing the top analyst coverage stocks, which implies that analyst coverage does not explain diffusion of information about a firms supply chain connections. A detailed description of the test for alternative explanations is provided in the Appendix.

Table 1.1: Summary Statistics of the Supply Chain Data

	SPLC	CRSP	% Coverage of CRSP
Panel A: Firms			
Number of all firms	2,152	5,090	42.3
Number of supplier firms	1,576	-	31.0
Number of customer firms	1,496	-	29.4
Market value of all firms (million \$)	14,229,214.35	18,983,256.21	75.0
Market value of suppliers (million \$)	11,622,294.74	-	61.2
Market value of customers (million \$)	13,085,195.03	-	68.9
Mean size of all firms (million \$)	6,740.00	4,497.34	-
Mean size of suppliers (million \$)	7,498.25	-	-
Mean size of customers (million \$)	8,901.49	-	-
Median size of all firms (million \$)	1,112.18	577.01	-
Median size of suppliers (million \$)	1,048.68	-	-
Median size of customers (million \$)	1,827.66	-	-
Panel B: links			
Number of links captured	11,819	-	-
Number of sales contribution $\geq$ 10%	865	-	-
Number of sales contribution $<$ 10%	10,954	-	-
Mean supplier / customer per firm	5.16	-	-
Median supplier / customer per firm	1	-	-
Out-degree power-law coefficient r	1.88†	-	-
In-degree power-law coefficient r	2.76†	-	-
% Equal weighted sales captured	16.09	-	-
% Revenue weighted sales captured	11.01	-	-

† Power law coefficients are fit to the function $N(k) = k^{-r}$ (meaning the probability for a node to have no smaller than k degrees) by maximum likelihood using the goodness-of-fit based method described in Clauset et al. (2009).

Notes. The SPLC column lists cross-sectional observations as of June 2, 2013. The CRSP column provides cross-sectional observations of 2012 annual fundamentals. The percent coverage is the number of stocks with a valid supplier-customer link in SPLC divided by the total number of CRSP stocks. The market cap percent coverage is the total market capitalization of stocks with a valid supplier-customer link in SPLC divided by the total market value of the CRSP stock universe. Size is the firm's market value of equity.

Table 1.2: Top 10 Most Connected Firms in US Supply Chain Network.

Rank	in-degree	k	out-degree	k	Total degree	k
1	Wal-Mart	249	Oracle	110	Wal-Mart Stores	249
2	Target	152	VMware	107	IBM	228
3	Hewlett-Packard	150	Microsoft	83	Hewlett-Packard	214
4	IBM	145	IBM	83	Cisco Systems	201
5	Lockheed Martin	140	Kansas City Southern	76	Microsoft	177
6	Boeing	138	Rackspace Hosting	74	Dell	171
7	Cisco Systems	132	Salesforce.com	74	Boeing	156
8	Dell	127	Manhattan Associates	74	Target	152
9	Costco Wholesale	126	Citrix Systems	72	Lockheed Martin	147
10	CVS Caremark	117	Cisco Systems	69	Oracle	139

Table 1.3: Pooled OLS of Concurrent and Lagged Returns.

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$	Adj.R^2(%)
Coef	0.000	-0.028***	0.025**	0.007	0.370***	0.387***	19.04
(T-Stat)	(0.49)	(-3.78)	(2.42)	(0.56)	(36.48)	(31.98)	
Coef	0.008***	-0.036***	0.044***	0.010			0.13
(T-Stat)	(9.10)	(-4.30)	(3.80)	(0.72)			
Coef	0.008***	-0.021***					0.03
(T-Stat)	(9.45)	(-2.81)					
Coef	0.008***		0.030***				0.04
(T-Stat)	(9.14)		(2.96)				
Coef	0.008***			0.013			0.00
(T-Stat)	(9.11)			(1.08)			
Coef	0.004***				0.517***		14.45
(T-Stat)	(5.16)				(55.65)		
Coef	0.001					0.587***	13.09
(T-Stat)	(0.91)					(52.56)	
Coef	0.004***		0.022**		0.517***		14.47
(T-Stat)	(5.02)		(2.32)		(55.61)		
Coef	0.001			0.002		0.587***	13.09
(T-Stat)	(0.88)			(0.21)		(52.54)	
Coef	0.000				0.370***	0.387***	18.98
(T-Stat)	(0.54)				(36.52)	(32.03)	

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the pooled OLS result of the regression (1) using concurrent supplier and customer returns, supplier and customer lagged effect, as well as firm's own lagged effect. The result shows that the concurrent supplier returns, the concurrent customer returns, the own lagged effect and the supplier lagged effect are significant in explaining firm returns, but not the customer lagged effect. The result is consistent for both univariate and multivariate regressions.

Table 1.4: Fama-MacBeth Regression of Concurrent Returns and Momentum.

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	-0.001	-0.088***	0.036**	0.024	0.399***	0.755***
(T-Stat)	(-0.96)	(-11.06)	(2.17)	(0.95)	(20.90)	(3.12)
Ave. Coef	0.009***	-0.090***	0.057***	0.004		
(T-Stat)	(10.38)	(-9.08)	(2.96)	(0.09)		
Ave. Coef	0.009***	-0.047***				
(T-Stat)	(10.53)	(-6.96)				
Ave. Coef	0.008***		0.022**			
(T-Stat)	(11.09)		(1.83)			
Ave. Coef	0.008***			-0.040		
(T-Stat)	(10.92)			(-0.66)		
Ave. Coef	0.003***				0.619***	
(T-Stat)	(3.61)				(37.25)	
Ave. Coef	-0.002**					0.992***
(T-Stat)	(-2.26)					(4.54)
Ave. Coef	0.004***		0.018*		0.625***	
(T-Stat)	(4.51)		(1.57)		(36.44)	
Ave. Coef	-0.002*			0.001		1.001***
(T-Stat)	(-1.92)			(0.0274)		(4.51)
Ave. Coef	-0.001*				0.393***	0.744***
(T-Stat)	(-1.80)				(22.48)	(3.20)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results of the regression (1) using concurrent returns and one-month momentum as independent variables. We have the same result as the pooled OLS after controlling for the time effect, i.e., the concurrent supplier returns, the concurrent customer returns, the own momentum and the supplier lagged effect are significant in explaining firm returns. The result is consistent for both univariate and multivariate regressions.

Table 1.5: Fama-MacBeth Regression after Controlling for Common Factors.

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	-0.000	-0.086***	0.063***	0.010	0.111***	0.503*
(T-Stat)	(-0.45)	(-9.16)	(3.42)	(0.23)	(4.28)	(1.78)
Ave. Coef	-0.001	-0.091***	0.050***	0.029		
(T-Stat)	(-1.09)	(-10.43)	(3.02)	(0.70)		
Ave. Coef	-0.002*	-0.054***				
(T-Stat)	(-1.80)	(-7.93)				
Ave. Coef	-0.001		0.029**			
(T-Stat)	(-1.60)		(2.29)			
Ave. Coef	-0.002**			0.034*		
(T-Stat)	(-2.50)			(2.05)		
Ave. Coef	-0.001**				0.126***	
(T-Stat)	(-1.75)				(6.24)	
Ave. Coef	-0.002***					0.501*
(T-Stat)	(-2.83)					(1.69)
Ave. Coef	-0.001		0.029**		0.130***	
(T-Stat)	(-0.886)		(2.14)		(5.93)	
Ave. Coef	-0.003***			0.041		0.492**
(T-Stat)	(-2.91)			(1.66)		(2.19)
Ave. Coef	-0.002***				0.114***	0.485*
(T-Stat)	(-2.16)				(5.45)	(1.79)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results after controlling for common asset pricing factors. We have similar results to those in Table 4. The results are consistent for both univariate and multivariate cases. All factors are defined by self-financing portfolio. Factor data is from the Kenneth French data library.

Table 1.6: Fama-MacBeth Regression of Alternative Explanations.

Filter Criteria	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Market	0.065***	-0.091***	0.070**	0.025	0.391***	0.370***
Capitalization	(6.29)	(-5.99)	(2.77)	(0.88)	(15.18)	(12.92)
	0.014***	-0.103***	0.105***	0.045		
	(14.87)	(-5.21)	(3.14)	(1.27)		
Institution	0.002*	-0.090***	0.084***	0.027	0.414***	0.566***
Ownership	(1.77)	(-6.84)	(3.45)	(0.79)	(13.14)	(14.07)
	0.013***	-0.101***	0.119***	-0.003		
	(10.09)	(-5.71)	(3.89)	(-0.08)		
Analyst	-0.000	-0.081***	0.047**	-0.007	0.377***	1.024*
Coverage	(-0.11)	(-6.49)	(2.25)	(-0.17)	(16.15)	(1.89)
	0.008***	-0.077***	0.071***	-0.067		
	(7.94)	(-4.95)	(2.90)	(-0.75)		
Trading	0.000	-0.081***	0.054**	0.060	0.429**	0.887***
Volume	(0.30)	(-7.94)	(2.53)	(0.17)	(17.39)	(2.41)
	0.010***	-0.081***	0.087***	-0.045		
	(8.56)	(-6.32)	(3.45)	(-0.69)		

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth robustness test results after filtering market capitalization (ME), i.e. $ME_i > \sum_j w_{ij}^{in} ME_j$, institution ownership, i.e. $\left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in} \left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_j$, analyst forecast, i.e. $AnalystForecastCount_i > \sum_j w_{ij}^{in} AnalystForecastCount_j$, and trading volume, i.e. $\left(\frac{TradingVolume}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in} \left(\frac{TradingVolume}{TotalShareOutstanding}\right)_j$. Institution ownership data is from Thomson-Reuters Institutional Holdings (13F) Database. Analyst coverage data is from the IBES dataset. Share trading volume data comes from the CRSP dataset.

The supplier lead-lag effect is also documented in the appendix of Cohen and Frazzini (2008). They use 30 years of Compustat data from 1980 to 2004, which is not overlapped with our data and thus serves as an out-of-sample test to our finding.

1.4.3 Backtest

Since the above results suggest that the one-month supplier lagged effect has predictive power for firms' returns, we perform a backtest using a value-weighted portfolio based on the following supplier prediction strategy. Specifically, every month we rank the firms according to their one-month supplier lagged effect and assign them to one of five quintile portfolios. All stocks are value weighted within a given portfolio and rebalanced every month. The strategy is to build a zero-cost portfolio that longs the top quintile supplier lagged effect stocks and shorts the bottom quintile supplier lagged effect stocks. This investment rule should earn zero abnormal returns in an efficient market.

We present the result in Table 1.7. We compute the abnormal returns using several definitions, including the excess returns above market, and the alpha in factor models. The rightmost column shows that this strategy delivers an excess return of 0.62% per month. After controlling for the four factors, it delivers an abnormal return of 0.56% per month or approximately 6.7% per year. This result is highly statistically significant, suggesting the economic magnitude of the supplier lagged effect is large.

1.4.4 Industry Breakdown

After examining the whole market, we wish to test whether similar results can be found for each industry sector since different industries may have different sensitivities to supplier and customer concurrent returns and lagged effects. Using the NAICS codes, we conduct Fama-MacBeth regressions for each industry. We use the first two digits of the NAICS code to identify large sectors to strike a balance between fine-grained industry classifications and statistical reliability. Note that the NAICS codes for a few firms tend to change over our chosen monthly window. For example, Cameron International Corporation (ticker CAM), a firm that provides flow equipment products, systems, and services worldwide, has its NAICS code as 332912 (Fluid Power Valve and Hose Fitting Manufacturing) in June 2011, while the code changes to 423830 (Industrial Machinery and Equipment Merchant Wholesalers) in July 2011. For sake of simplicity, we use the NAICS code as of December 31, 2012.

The results appear in Table 1.8. The number of firms in each industry is recorded in the second column. Note that there are 2,139 firms in total in Table 1.8, fewer than the 2,152 firms in our data set. This is because some industry sectors, such as Education Services (NAICS code 61) and Public Administration (NAICS code 92), have fewer than 5 firm observations captured in our data and are thus excluded from consideration in this study. A few firms also have an industry code listed as “Non-Classified” and are thus omitted. From the results, we can assign most industries to one of two groups: Group 1 (those with concurrent relationship effects and supplier lagged effects) and Group 2 (those without supplier lagged effects).

Table 1.7: Supplier Prediction Strategy, Abnormal Returns (%)

	1(Low)	2	3	4	5(High)	L/S
Excess returns	-0.09	-0.09	0.37	0.47	0.53	0.62*
(T-Stat)	(-0.05)	(-0.06)	(0.27)	(0.42)	(0.40)	(1.69)
CAPM	-0.45	-0.49	-0.28	0.06	0.16	0.61**
(T-Stat)	(-1.06)	(-1.48)	(-0.89)	(0.66)	(0.33)	(2.25)
Three-factor	-0.39	-0.40	-0.28	0.06	0.16	0.55**
(T-Stat)	(-0.86)	(-1.05)	(-1.52)	(0.14)	(0.44)	(2.10)
Four-factor	-0.41	-0.42	-0.30	0.12	0.15	0.56**
(T-Stat)	(-0.91)	(-1.06)	(-1.59)	(0.29)	(0.39)	(2.09)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the backtest result using the supplier prediction strategy. The zero-cost portfolio constructed by holding the top quintile and selling short the bottom quintile yields significant abnormal returns as is shown in the rightmost column. Every quintile portfolio has 352 firms.

Table 1.8: Fama-MacBeth Regression of Industry Breakdowns

NAICS	# Firms	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
11	6	0.021***	-0.209**	0.297*	-1.048	0.412***	0.204**
Agriculture & Forestry		(3.38)	(-2.74)	(1.47)	(-1.52)	(72.15)	(2.49)
21	127	-0.011	-0.136***	0.035	0.030	0.597***	0.516***
Mining		(-2.18)	(-3.34)	(0.32)	(0.30)	(7.13)	(3.90)
22	52	0.013***	-0.163**	0.184**	-0.044	0.199	0.065
Utilities		(4.07)	(-2.63)	(1.85)	(-0.91)	(1.50)	(0.52)
23	18	-0.008	-0.093	0.101	0.100	0.747***	0.642**
Construction		(-0.61)	(-1.00)	(0.36)	(1.00)	(3.81)	(6.29)
31-33	1041	-0.003	-0.085***	0.024*	0.044*	0.376***	0.969**
Manufacturing		(-2.31)	(-8.04)	(1.73)	(1.68)	(17.05)	(2.26)
42	59	0.012***	-0.096**	-0.057	0.042	0.698***	0.230**
Wholesale Trade		(3.33)	(-2.03)	(-0.40)	(0.36)	(4.41)	(2.04)
44-45	146	0.006	-0.116***	-0.040	0.046	0.493***	0.392***
Retail Trade		(0.15)	(-4.19)	(0.38)	(0.58)	(4.48)	(4.87)
48-49	79	-0.002	-0.040	0.100*	-0.079	0.438***	0.513***
Transportation & Warehousing		(-0.28)	(-0.80)	(1.72)	(-0.69)	(4.77)	(3.02)
51	245	0.001	-0.076***	0.087**	-0.079	0.319***	0.544***
Information		(0.54)	(-3.22)	(2.09)	(-1.62)	(6.69)	(8.16)
52	45	0.013	-0.069	-0.142	0.063	0.361**	0.503**
Finance & Insurance		(1.27)	(-0.59)	(-0.65)	(0.76)	(2.49)	(1.99)
53	33	0.012	-0.014	0.060	-0.012	0.516***	0.694***
Real Estate, Rental & Leasing		(2.51)	(-0.19)	(0.47)	(-0.09)	(3.43)	(3.43)
54	159	-0.001	-0.099***	0.050	0.071	0.422***	0.478***
Professional, Science & Tech		(-0.24)	(-3.56)	(0.78)	(0.79)	(4.94)	(5.72)
56	46	0.006	-0.116**	-0.096	0.262**	0.031	0.607***
Support, Waste & Remediation		(0.88)	(-2.09)	(-0.84)	(1.90)	(0.12)	(3.22)
62	39	-0.012	-0.181***	0.271*	-0.005	0.884***	0.930***
Health Care & Assistance		(-1.13)	(-2.90)	(1.74)	(-0.02)	(2.59)	(2.68)
71	14	0.007	-0.057	0.032	-0.035	0.499***	0.427
Arts, Entertainment & Recreation		(1.59)	(-0.70)	(0.498)	(-0.413)	(4.82)	(1.60)
72	30	0.029***	-0.111	0.086	-0.177	0.558***	0.091
Accommodation & Food Service		(3.03)	(-1.59)	(0.31)	(-0.45)	(3.04)	(0.32)

*p-value<10%, **p-value<5%, ***p-value<1%

*Notes.*This table summarizes the Fama-MacBeth results at the industry level using the first 2 digits of the NAICS codes (1997 standard).

Group 1 has the same results as in Tables 1.3-B.1, that concurrent upstream and downstream returns as well as the supplier lagged effect are significant. Group 1 includes Agriculture & Forestry (NAICS code 11), Manufacturing (NAICS code 31-33), Transportation & Warehousing (NAICS code 48-49), Information (NAICS code 51), and Health Care (NAICS code 62). This group has a total of 1,413 firms which is 66% of the sample size and more than 60% of the U.S. economy. Thus, Group 1 drives our result for the economy-wide observations in Tables 3-5. We note that Manufacturing (NAICS code 31-33) in this group also has a weakly significant customer lagged effect.

Group 2 only has concurrent effects and no lagged effects. Group 2 includes Mining (NAICS code 21), Construction (NAICS code 23), Wholesale (NAICS code 42) and Retail (NAICS code 44-45), Finance & Insurance (NAICS code 52), Real Estate & Leasing (NAICS code 53), Professional & Science (NAICS code 54), and Arts & Entertainment (NAICS code 71).

Other sectors exhibit unique behavior. Specifically, Utilities (NAICS code 22) are sensitive to suppliers' concurrent performance and one-month lagged effect, but not to customer effects. One possible reason may be that they are sensitive to the prices of their input materials such as oil and gas, but the downstream demand is relatively stable since their customer base is well diversified. Support, Waste & Remediation (56) seems to only have statistically significant relations with downstream customers and not with suppliers. This may be due to the fact that their market performance is mainly determined by the quantity of services purchased by downstream firms. Accommodation & Food (NAICS code 72) is only sensitive to its concurrent supplier performance, possibly because their major customers, household consumers, are omitted from our consideration. Note that the supply chain relationship is not a major factor for firms in some industries such as finance and insurance, so some results here are exploratory but included for completeness.

1.5 Summary and Directions

1.5.1 Summary of the Findings

In this chapter, we find evidence that supply chain network structure and firm returns are closely connected and that firms' supply chain relationships can explain this measure of supply chain performance, assuming that the supply chain structure is fixed in the short run. Firm returns are influenced by the first-order effect of their supply chain partners' performance. With a network model of firm returns, we find that concurrent returns of both suppliers and customers are significant in explaining a firm's returns. We also observe significant lead-lag relationships from the firm's own lagged effect and the suppliers' lagged effect, but not from a customer lagged effect. A long-short equity strategy based on the supplier lagged effect yields monthly abnormal returns of 56 basis points. The cross lagged effect results have several important implications for returns information diffusion in supply chain networks.

From the financial market perspective, this result may indicate investors' limited attention to suppliers. Another possible reason is that supplier information is generally harder to obtain than customer information, since firms are more reluctant to disclose suppliers than customers, perhaps to protect proprietary suppliers from competitor firms.

From the operations management perspective, this result may indicate that the supply chain generally coordinates better in the upstream than in the downstream direction. Customer firms may not know all of their supplier's information until the one-month lag has elapsed. The result may also indicate larger market power for supplier firms in the supply chain than customer firms. Another possible explanation is that customer firms may order less foreseeing a demand shock, causing supplier firms to show a decrease in revenue ahead of customer firms due to input delivery lead time.

We observe some variation in the results across different sectors. Possible reasons for these observations may be that some industries have better supply chain coordination than others or that investors may pay more attention to supply chain information in certain industries so that those industries only have significant concurrent supply and customer effects. For firms with insignificant concurrent cross-firm effects, their major suppliers and customers may reside in economic sectors beyond the scope of this paper, i.e., private firms, government, household, or the foreign sector.

For managerial implications, our results suggest that managers should be aware of both the concurrent effects from the direct connections to their customers and suppliers on their firm's returns performance, as well as the suppliers' previous performance. This study mainly focuses on the tier-1 supply chain shock on firm performance. In unreported tables, we find supply chain shocks can affect a supplier or customers as far as 3 tiers away. Therefore, another managerial implication is that the manager should care about the operation of its suppliers and customer firms multiple tiers away, which is in accordance with the theoretical implications from Ang et al. (2015).

In unreported tables, we also check the performance impact from the characteristics of supply chain relationships including the following ones.

1. Firm Market Power:

   Market power facilitates the firm's ability to adjust price and quantity upon news in the supply. A proxy for the market power is the ratio of firm size to the industry size, defined by the market capitalization. Using this definition, we find firms with lower market power are affected more by supply chain shocks due to the inflexibility to adjust price and quantity.

2. Supplier Substitutability:

   Supplier substitutability allows the firm to use the capacity of another supplier when one supplier is disrupted. A proxy for the supplier substitutability is the ratio of the purchase value on one supply chain to the total cost of good sold (COGS). Using this definition, we find firms with less substitutable supplier are affected more by supplier shocks.

3. Inventory Level: Inventory serves as a buffer against supply chain shocks. A proxy for the inventory level is the ratio of raw inventory to the firm's total asset. Using this definition, we find firms with lower inventory level are affected more by supplier shocks.

4. Supply Chain Financing: Trade credit is the credit extended by a supplier firm to a customer firm, facilitating the purchase of goods and services without immediate payment. However, when the customer is disrupted, the supplier firm is more susceptible to the supply chain shocks due to the higher probability of trade credit default. A proxy for the trade credit level is the ratio of account receivable to the firm's total asset. Using this definition, we find firms with more credit level are affected more by customer shocks.

1.5.2 Empirical Extensions

In line with the firm performance in supply chain networks, there are several other different angles to examine this question. We list two directions below as extensions.

Event Study on Propagation Channel

One angle is to study the fundamental channels causing the propagation of performance shock, such as firm operations and financial news that would affect its supply chain partners. We can form an event list consisting of different event types that are intuitively related to both supplier and customer companies, then analyze their propagation impact[8]. For one

8. S&P Capital IQs Key Developments and Future Events (KDFE) is a structured event database that provides many different event, mostly on financial and accounting news. Most operations news data is

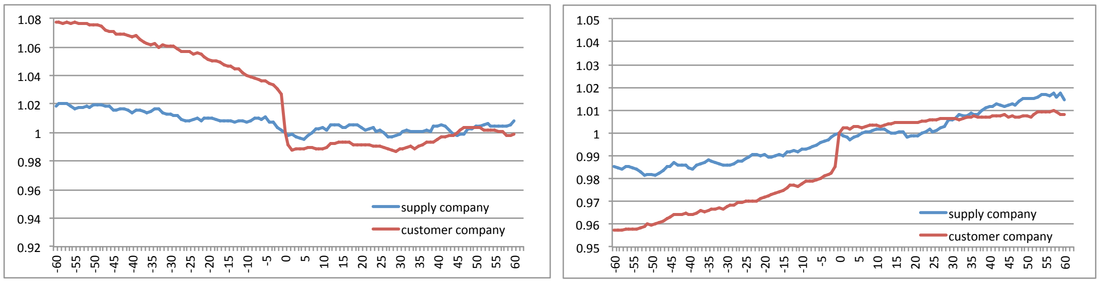


Figure 1.7: Guidance Event Propagation on Supply Chain (Left: Guidance Lowered, Right: Guidance Raised).

type of example event, Hendricks and Singhal (2003) focus on operation disruption and find propagation of such news in the supply chain. For another type of example event, guidance reports issued by companies on future earnings can have significant influence over analysts stock rating price target, as we can see from the aforementioned example that Coastcast stock price drops after Callaway earnings forecast miss.

We use linkages that have the largest revenue contribution from the Compustat segment data, which has time series information. We investigate stock price trend 60 days prior and post the event occurrence date. We use the official announcement date as day zero and analyze the cumulative wealth. The results in Figure 1.7 show that when a company lowers its guidance, the companys share price drops as well as its suppliers share price; similarly, after a company raises its guidance, the companys share price rises as well as its supplier's share price.

There are many potential events that can serve as channels for shock propagation in the supply chains. A comprehensive list of events is difficult to acquire as the traditional event study technique often select event types arbitrarily. Big data and machine learning technique such as Latent Dirichlet Analysis (LDA) based on semantic recognition of unstructured textual data may be a systematic method to answer what events are important for shock propagation.

unstructured.

CDS Measure for Credit Shocks

Equity market price is useful in several applications as it captures the average shocks, but it is limited for tail risk measurement and extreme shocks. How do extreme shocks such as credit events transfer to partners in the supply chain? To study this question, we need to use another measure, the credit default swap (CDS). CDS is a clean and direct measure of a firm's credit risk, and the CDS market provides a high-quality data source.

We look at both events of the extreme upward and downward jumps in CDS spreads, which are largely unanticipated credit events. A jump-up (down) event means the increasing (decreasing) probability of the subject firm going default on its debt obligation, which shows its operations is worsening (improving), and which is likely to affect its upstream suppliers and downstream customers.

To identify jump-up events, we consider all changes in daily CDS spreads above the 99.9% value, similar as Jorion and Zhang (2009). Likewise, to identify jump-down events, we consider all changes in daily CDS spreads below the 0.01% value. CDS jump event should have a positive contagion effect on supply chain partners (both supplier and customer firms). Thus the main hypothesis is the following.

Hypothesis 4. *CDS jump-up event should lead to wider CDS spreads for both upstream suppliers and downstream customers.*

Hypothesis 5. *CDS jump-down event should lead to narrower CDS spreads for both upstream suppliers and downstream customers.*

We use Markit data for daily CDS data and FactSet Revere for supply chain data. After merging the two datasets, we have coverage of the period from April 2003 to December 2014. We use 5-year long-term CDS spreads because these contracts are the most liquid and some short term noises and be avoided. After we construct the daily CDS jump events using the above definition, we construct the CDS change of the equal-weighted supplier and customer portfolios of such event firms in a 11-day window, i.e. the equal weighted supplier and customer portfolio cumulative CDS spread changes (CSCs). The cross-sectional mean for all CSCs are reported in Table 1.9. We can see that the credit shock shown in the CDS jump event affects both supplier firms and customer firms significantly on a 3-day window or a 11-day window centered at the event day.

One concern we may have is that firms in certain credit rating category are more likely to have CDS jump events. Therefore, to justify the credit shock contagion it is necessary to control for different credit rating groups. We calculate the rating-neutral excess CDS spread by subtracting the average CDS spreads of the group with the same credit rating lagged by one day[9]. The results is shown in Table 1.10, slightly weaker than 1.9 but still significant. For jump-up events, the average CSC is 18 bp (54 bp) for the 3-day (11-day) window. For jump-down events, the average CSC is -24 bp (-66 bp) for the 3-day (11-day) window. Credit shocks also seem to cluster by industry sectors. In unreported table, we also add controls for industry sectors and the results hold the same qualitatively.

9. We use one-day lag to construct the credit rating groups because the subject firm's credit rating could be changed on the event date

Table 1.9: Credit Shock Propagation after CDS Jump Event (Left: Jump-up Events, Right: Jump-down Events).

Jump-up	Customer CSC		Supplier CSC		Jump-down	Customer CSC		Supplier CSC	
#Portfolio	258		292		#Portfolio	258		292	
Day	Mean	t-stat	Mean	t-stat	Day	Mean	t-stat	Mean	t-stat
-5	0.0014	2.31**	-0.0001	-0.11	-5	-0.0011	-1.50	0.0007	0.98
-4	0.0004	0.73	0.0015	1.85	-4	-0.0016	-2.60***	-0.0001	-0.32
-3	0.0012	1.36	-0.0005	-0.87	-3	-0.0008	-1.66*	-0.0003	-0.68
-2	0.0018	2.46**	0.0011	1.41	-2	-0.0003	-0.50	-0.0002	-0.38
-1	0.0018	2.84***	0.0015	2.26**	-1	-0.0015	-2.19**	-0.0005	-1.12
0	0.0016	1.85*	0.0013	1.91**	0	-0.0022	-3.57**	-0.0020	-3.20***
1	0.0009	1.20	0.0008	1.02	1	-0.0010	-1.50	-0.0008	-1.52
2	0.0006	0.95	0.0005	0.87	2	-0.0003	-0.53	-0.0002	-0.28
3	-0.0010	-1.30	0.0008	0.68	3	0.0001	0.14	-0.0003	-0.55
4	0.0001	0.09	0.0013	1.57	4	-0.0003	-0.70	0.0002	0.32
5	0.0001	0.14	-0.0011	-0.93	5	-0.0005	-1.03	0.0002	0.59
[-1,1]	0.0025	2.01**	0.0020	1.64	[-1,1]	-0.0033	-3.59***	-0.0028	-3.12***
[-5,5]	0.0075	2.88***	0.0069	2.95***	[-5,5]	-0.0083	-3.36***	-0.0041	-1.58

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. CDS data is from Markit. Supply chain information is from FactSet Revere. The periods tested is from April 2003 to December 2014. CSC is the portfolio cumulative CDS spread changes.

Table 1.10: Credit Shock Propagation after CDS Jump Event Controlling for Credit Ratings (Left: Jump-up Events, Right: Jump-down Events).

Jump-up	Customer CSC		Supplier CSC		Jump-down	Customer CSC		Supplier CSC	
#Portfolio	258		292		#Portfolio	258		292	
Day	Mean	t-stat	Mean	t-stat	Day	Mean	t-stat	Mean	t-stat
-5	0.0008	1.34	-0.0003	-0.33	-5	-0.0007	-0.90	0.0007	1.10
-4	-0.0001	-0.23	0.0014	1.79*	-4	-0.0014	-2.34**	-0.0002	-0.55
-3	0.0010	1.10	-0.0006	-1.02	-3	-0.0007	-1.57	-0.0005	-0.94
-2	0.0015	2.07**	0.0009	1.19	-2	-0.0006	-0.92	-0.0008	-1.35
-1	0.0010	1.49	0.0012	1.93*	-1	-0.0014	-1.99**	-0.0005	-1.10
0	0.0011	1.26	0.0006	0.92	0	-0.0016	-2.56**	-0.0017	-2.68***
1	0.0007	0.95	0.0003	0.45	1	-0.0008	-1.02	-0.0007	-1.45
2	0.0004	0.58	0.0002	0.32	2	-0.0016	-1.33	-0.0011	-0.99
3	-0.0006	-0.78	0.0006	0.52	3	0.0018	1.31	-0.0003	-0.56
4	-0.0011	-0.82	0.0011	1.40	4	-0.0002	-0.34	0.0003	0.45
5	0.0014	1.07	-0.0011	-0.96	5	-0.0002	-0.40	0.0003	0.58
[-1,1]	0.0018	1.46	0.0009	0.77	[-1,1]	-0.0024	-2.46**	-0.0024	-2.273***
[-5,5]	0.0054	2.08**	0.0044	1.98**	[-5,5]	-0.0066	-2.67***	-0.0053	-1.99**

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. CDS data is from Markit. Supply chain information is from FactSet Revere. The periods tested is from April 2003 to December 2014. CSC is the portfolio cumulative CDS spread changes.

CHAPTER 2

SYSTEMATIC RISK IN SUPPLY CHAIN NETWORKS

2.1 Introduction

The second question we address is related to systematic risk as a second-order factor in risk transmission reflecting global properties of the network. The standard asset pricing models suggest that exposure to systematic risk determines stocks' expected returns. Those models, including the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama-French three-factor model, and the extension to a fourth factor by Carhart (1997), all propose common factors that measure firms' exposure to systematic risk. CAPM treats the market risk as the factor of non-diversifiable risk, generally proxied by the market premium, the difference between the market return and the risk-free rate. Those components of returns that cannot be explained by CAPM have been traditionally referred to as "anomalies," among which the most well known are the size effect, the value effect, and momentum. Recognition of the size effect dates back at least to Banz (1981), who finds that average returns on small stocks are too high in the cross-section of returns given their market betas. The value effect is first recorded by Rosernberg et al. (1985), who find that average returns of stocks in the cross-section are positively related to the ratio of a firm's book value to its market value. Building on these observations, Fama and French (1993) proposed the three-factor model including a portfolio's exposure to the small-cap class and the high book-to-market ratio class. The additional momentum effect refers to the positive relation between an asset's current returns and its recent historical performance, which is based on the observation that stocks that performed relatively well in the past tend to have higher returns in the short run. Momentum was first studied by Jegadeesh and Titman (1993) and was incorporated as a fourth factor by Carhart (1997).

Even though the standard asset pricing models explain a portfolio's return quite well, other factors (in particular, liquidity as shown in Pástor and Stambaugh (2003)) may also influence systematic risk. More importantly, since the standard asset pricing models generally identify risk using ex-post correlation between a portfolio's returns and market factors, they do not reason the ex-ante determinants of a firm's exposure to systematic risk. To address this question, we argue that the correlated supply chain relationships in aggregate determine systematic risk. Specifically, holding the supply chain network structure sufficiently stable for a short period of time, this structure is an exogenous and ex-ante identifiable source of cross-sectional variation. In line with this logic, the fundamental assumption we make is that a firm's systematic risk is formed from the aggregation of idiosyncratic shocks, which are likely to be transmitted to supply chain partners. Recent theoretical and empirical evidence supports this view. Based on a theory of network transmission of sectoral shocks, Acemoglu et al. (2012), for example, show that microeconomic idiosyncratic shocks may lead to aggregate fluctuations. In addition, Carvalho and Gabaix (2013) present empirical evidence that volatility in aggregate national output is driven by sectoral shocks. Kelly et al. (2013) also show evidence that the supplier chain network is an important determinant of firm-level volatility. While these observations at aggregate levels give an indication of systematic risk transmission at aggregate levels, they do not address how shocks propagate across individual firms and how firms' operational decisions about suppliers are related to risk mitigation motives. This paper aims to help fill this information gap.

Using a network constructed by the supply chain connections to understand systematic risk is appealing because it mirrors the intuition of most asset pricing models, where systematic risk is not driven by an asset's own idiosyncratic risk. Instead, an asset's exposure to systematic risk is based on its relationship with the entire economy. Following this logic, the underlying source of systematic risk should also reflect the relationship between an asset's economic fundamentals and overall economic fundamentals. This relationship is precisely what the supply chain network captures. The position of a firm in the supply chain network can be constructed as a proxy for its exposure to the overall economy.

To address the hypothesis that supply chain network structure is associated with systematic risk, we group firms in quintiles according to their network centrality. The most similar research to ours is that of Ahern (2013), which argues that industries that are more central in the economic network of intersectoral trade earn higher stock returns than industries that are less central. This is because, at the industry level, links are hardly substitutable; thus, operational hedging (substitution of different inputs or outputs in response to shocks) is difficult. Taking input links as an example, if an industry requires inputs from multiple other industries, it is exposed to higher risk because any shock to its supplier industries affects its production. However, we argue this finding may not be identical at the firm level since now links may be substitutable; thus, the correlation among idiosyncratic shocks matters at this level.

It has been well known that operational hedging can be used to mitigate idiosyncratic noise in the supply chain, as shown, for example, in Anupindi and Akella (1993). On one hand, if the idiosyncratic shocks of supply chain partners are positively correlated, a firm with more links is exposed to higher systematic risk due to aggregation of shocks; thus, it should have higher returns on average. On the other hand, if the idiosyncratic shocks of supply chain partners are hedged away due to their independence, a firm with more links is actually exposed to lower systematic risk and should have lower returns. Interestingly, both possible phenomena are observed in our results after controlling for common pricing factors and other alternative explanations. While more numerous suppliers and centrality are associated with lower returns for manufacturing firms, increased input links correlate with higher returns for logistics and transportation firms. We interpret these differences as manufacturers' relative ability to hedge and to take advantage of competencies not directly related to specific products (as shown in Atalay et al. (2014)).

The questions examined in Chapter 1 and Chapter 2 can be unified in the basic net present value formula as follows, which determines a firm's valuation, as well as its return performance:

$$p_t = \sum_{s=0}^{\infty} e^{-(r_s+\delta_s)s} d_s, \tag{2.1}$$

where d_s is the expected dividend paid, r_s is the expected discount factor, and δ is the risk premium. The first-order effect changes in the expectations of a firm's performance in each future period, i.e. d_s. The second-order effect captures the exposure of that performance to market risk premium, i.e. δ_s, the firm faces. Those two effects together jointly affect a firm's returns. Our objective is to see how supply chain position and structure affect these two aspects of firm valuations.

The rest of the chapter is structured as follows. Section 2 introduces the empirical model and hypotheses for the second-order impact from systemic exposures through the network. Section 3 examines the empirical results. We show that more central manufacturing firms earn lower returns on average, while the opposite is true for logistics firms[1]. Section 4 concludes and suggests future research directions including the build-up of a theoretical firm level supply chain model.

2.2 Model of Systematic Risk in Supply Chain Network

In this section, we propose that network centrality in the supply chain network can explain firms' exposure to systematic risk. We hypothesize that some network positions may be aggregators of correlated idiosyncratic shocks, leading to higher systematic risk, while others may be connected to relatively independent sources, reducing systematic risk effects.

In this section, we investigate the supply chain network and firms' exposure to systematic

1. From now on, we use a broad definition of logistics firms to include all firms that add value in the logistics process such as the storage, transfer, and distribution to consumers, which includes firms in the transportation, wholesale, and retail sectors.

risk, the second-order impact of aggregate shocks across multiple relationship levels. We particularly model network centrality and its risk implications. Following the variety of patterns of shock transmission that appear in models such as in Acemoglu et al. (2012), we assume that some network positions may be aggregators of correlated idiosyncratic shocks while others have connections that tend to dissipate idiosyncratic shocks and reduce systematic risk.

Our fundamental underlying assumption is that a firm's systematic risk is formed from the aggregation of idiosyncratic shocks, which are then likely to be transmitted to their supply chain partners. Those idiosyncratic shocks may not be independent of each other and may be correlated exogenously. The exogenous correlation is irrelevant for the supply chain relationships, meaning that idiosyncratic shocks are correlated with each other even if there is no sales link between the firms. Geographical proximity and sector proximity are examples of such exogenous factors that may produce correlation, e.g., geographically close firms may tend to have correlated idiosyncratic shocks. An earthquake or regional political unrest is likely to affect all firms that operate in the area, regardless of their industrial sectors. Sector proximity, on the other hand, may produce correlation as firms in the same industry face similar changes in resources or technologies. For example, a discovery of a large gold mine would possibly affect all mining firms in precious metal, or the new release of a popular tablet or a smart phone may be a simultaneous negative shock to other competing firms. Therefore, even assuming the network structure is uniformly distributed, where the no-connection network and the fully connected network are two extreme cases, idiosyncratic shocks may not be independent of each other.

Firms can mitigate supply risk or demand risk by choosing partners with which the idiosyncratic shocks are less correlated. As we observed regarding Nokia, their having multiple supplier relationships apparently helped them absorb the shock of the Philips fire, which, while idiosyncratic, could have had a ripple effect, as in Acemoglu et al. (2012), across the economy. We suppose this may be the case for other manufacturing firms, which often seek multiple less correlated suppliers to provide input materials, i.e., multiple sourcing, and which tend to take advantage of efficient organizational processes to enter different levels of the supply chain even when those entries have no physical (direct input or output) connections to parts of the firm operating at upstream or downstream supply chain levels. This observation in Atalay et al. (2014) of the prevalence of firms with disconnected production units at distinct supply chain levels suggests a natural risk mitigation mechanism in manufacturing that reduces the systematic risk of a firm that creates such connections.

However, not all firms are able to diversify their suppliers or customers (e.g., diversifying geographically linked shocks) or to enter different levels of the supply chain that may mitigate sectoral risks, resulting in a systematic risk exposure. Firms in the logistics industry may be such examples. Logistics firms such as transportation and warehousing usually serve other businesses which are close in geographical or sector distance. Their input resources (direct equipment and supplies) may also be limited in geographical diversity as may be their abilities to employ their organizational capabilities from this industry at different levels of the supply chain. They also do not face the hold-up problem of a manufacturer, such as Ericsson, where a disruption to a single supplier can shut down all production. This multiplier effect creates an incentive for creating uncorrelated relationships that is not present for wholesalers, retailers, and logistics firms whose individual suppliers rarely can hold up all of their operations.

As noted, manufacturers also may have more opportunities than logistics firms to exploit management expertise in different sectors. For example, while an automotive components manufacturer may be able to exploit its manufacturing expertise to move up the supply chain to fabricate plastic molded parts, a trucking firm that consumes automotive components for service parts may not have a particular advantage in entering that or other supplier markets. For firms in the trucking company's position, idiosyncratic shocks at partners may be more likely to be correlated, thus causing a ripple effect. As a result, they may be exposed to higher risks if they are in more central positions of the logistic firms' supply chain network.

To illustrate better, we use the following model to show a demonstrative example. Suppose an economy with 2 regions (A and B) and 3 potential future states with equal probability $(Prob\,(S = S_i) = \frac{1}{3}, \forall i \in \{1, 2, 3\})$: S_1: both A and B function; S_2: A cannot produce while B can; S_3: B cannot produce while A can.

Next, suppose we have 4 firms in the economy, 3 manufacturers and 1 distributer. The manufacturers have limited production capacity and produce a payoff of 1 (due to the fixed production capacity) as long as one of their input regions functions. Firm 1, 2 and 3 are manufacturers. Firm 1 only sources input from region A, Firm 2 only sources input from region B, and Firm 3 sources from both regions. Firm 4 is the distributor which connects to both region A and region B with a fixed cost of 1 in all states. Therefore, in each of the states mentioned above, the payoff for these 4 firms are as given below:

$$\Pi_1 = \{1, 0, 1\}, \Pi_2 = \{1, 1, 0\}, \Pi_3 = \{1, 1, 1\}, \Pi_4 = \{1, 0, 0\}. \tag{2.2}$$

Suppose we have a representative mean-variance investor. Let $\mu = [\mu_1, \mu_2, \mu_3, \mu_4]$ denote the firms' expected return. Then we will have $\mu_3 < \mu_1 = \mu_2 < \mu_4$[2], i.e. the manufacturers have lower risk than the distributor, and the dual sourcing manufacturer is less risky than the single sourcing manufacturers.

In sum, our arguments support the presence of lower systematic risk for better connected manufacturing firms and higher systematic risk for more central logistics firms. We then state the following hypotheses.

Hypothesis 6. *For the manufacturing industry, more central firms earn lower stock returns on average due to their exposure to lower systematic risks.*

Hypothesis 7. *For the logistics industry, more central firms earn higher stock returns on*

2. See Appendix for proof

average due to their exposure to higher systematic risks.

We use equity returns over other metrics to focus on systematic risks alone since other factors such as product variety are endogenous in the returns information. In the next section, we present measures of centrality that we then use to test these hypotheses.

2.3 Empirical Results

To test the hypotheses concerning second-order effects and systematic risk, we group firms in the same large industry sectors (based on the first digit of the NAICS code) into five quintiles according to centrality, which can be measured in various ways.

Common measures to quantify centrality in networks include degree, closeness, betweenness, and eigenvector centrality. To use the correct measure for the sales in the supply chain network, we must consider the characteristics of importance that underlie each measure. Borgatti (2005) reviews these measures and classifies them based on characterization of network flows. First, network traffic could be assumed to follow a walk (both nodes and links can be repeated), a trail (a sequence in which no link is repeated), a path (a sequence in which no node is repeated), or a geodesic path (the shortest path between two nodes). Second, network traffic can be assumed to spread serially (through only one path at a time), or in parallel (through multiple paths at the same time).

Though making generalizations about firm level shocks is problematic, we can provide some reasoning about how shocks may be transmitted from one firm to another. First, firm level shock is unlikely to follow a geodesic path, i.e. the shortest distance, because firm level shocks that transmit across a supply chain network do not have final recipients and are unlikely to follow the shortest path between firms. According to Borgatti (2005), this means that closeness and betweenness centrality are inappropriate for economic shocks since they implicitly assume that traffic follows geodesic paths. Second, economic shocks are likely to have feedback effects. A supply shock in one firm could affect the supply of downstream firms, which eventually could transmit back to the original firm through the purchase orders or the reserve sales. For instance, a shock to a microchip plant may affect the downstream device manufacturer's fulfillment, which may result in future reduced orders to the microchip plant due to goodwill loss; and a shock to an oil firm could affect the cost of gasoline, which affects the costs of a transportation firm, which could then affect the oil firm itself. Just because a shock originated in a firm does not imply that it is immune from a subsequent feedback shock. Thus, supply chain network shocks are unlikely to be restricted to follow paths or trails, in which nodes and links are not repeated. Based on these assumptions, the most appropriate centrality metric for economic links is eigenvector centrality. As discussed in Bonacich (1972), eigenvector centrality is the principal eigenvector of the network's adjacency matrix. Nodes are more central if they are connected to other nodes that are themselves more central[3]. The linear relationship in eigenvector centrality also corresponds to the linear relationships of shock propagation shown in the first-order effect. Since eigenvector centrality cannot always be applied to asymmetric adjacency matrices (Bonacich and Lloyd (2001)), for simplicity, we make our sparse adjacency matrix symmetric by taking the maximum value of the upper and lower triangular components.

Since the eigenvector centrality measure is skewed, we take the log of centrality in these statistics. Figure 2.1 presents the histogram of log eigenvector centrality for all firms in SPLC, versus all manufacturing firms (NAICS 3) in SPLC, and all logistics firms (NAICS 4). The mean of centrality for SPLC is about 0.04%, while the mean for manufacturing and logistics are both about 0.05%. This means that the manufacturing and the logistics firms are relatively more central in the supply chain network than other firms on average, and a random shock that propagates through the network is likely to hit such a firm about 0.05% of the time. The histograms are slightly skewed negatively, reflecting the asymmetric nature of the network as discussed in Acemoglu et al. (2012).

3. In matrix notation, this is $Wc = \lambda c$, c is the principal eigenvector of the adjacency matrix.

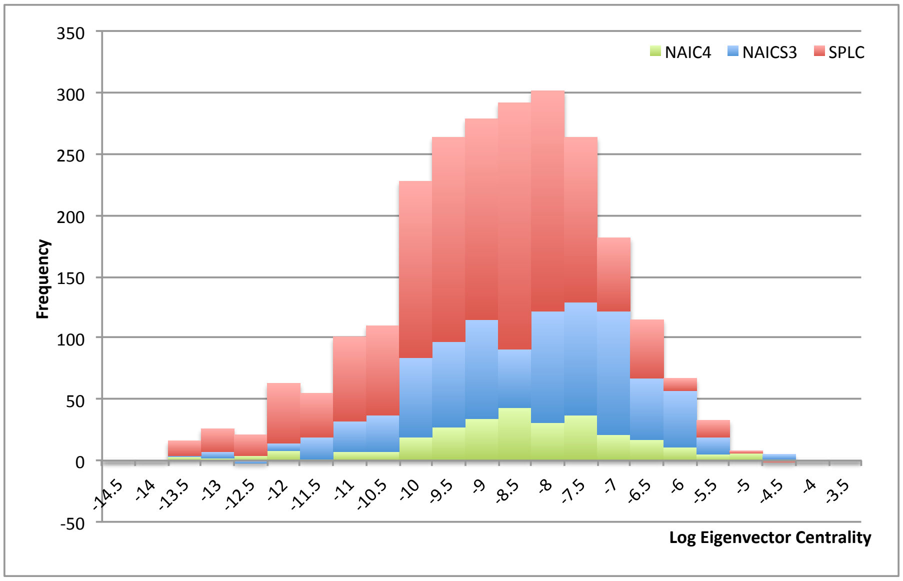


Figure 2.1: Distribution of Eigenvector Centrality

Apart from eigenvector centrality, and the closeness and betweenness centrality we have excluded, we test in-degree centrality (i.e., the number of suppliers) and out-degree centrality (i.e., the number of customers), which are proxies to the supplier multiplicity and the customer multiplicity. We are able to find a salient significant trend for in-degree centrality, but not for out-degree centrality, implying that the number of suppliers is associated with a firm's exposure to systematic risks, but not necessarily the number of customers. Due to data limitations, higher order network importance measures such as Herfindahl concentration may be misleading. After testing using the supplier Herfindahl concentration and customer Herfindahl concentration from our data, we do not find significant results in trends, and, therefore, only present results for eigenvector centrality and in-degree centrality.

In our dataset, 1041 firms fall into the manufacturing industry (NAICS code 31-33). We delete stocks with a price less than 5 dollars per share to avoid large liquidity effects and then sort firms into five quintiles based on the chosen centrality. The availability of the stock prices limits the sample size to 716 firms; therefore, each portfolio in the manufacturing industry group contains 143 firms.

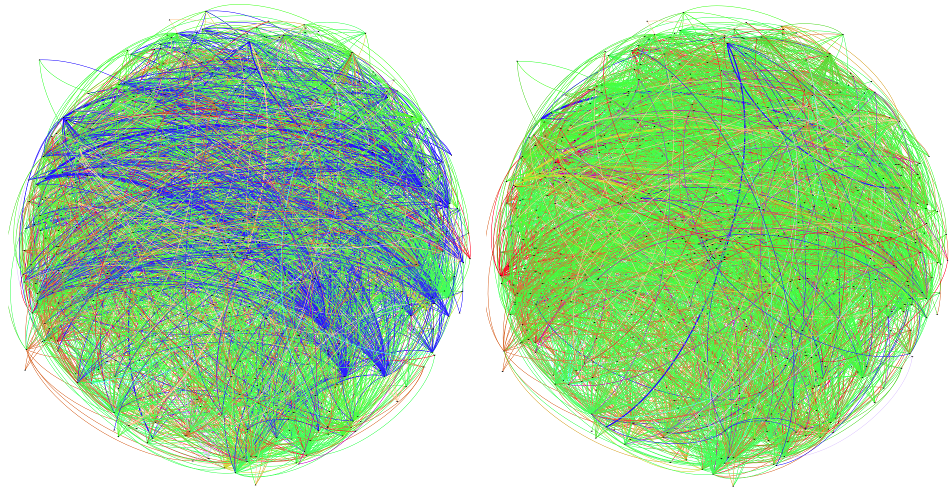


Figure 2.2: Industry of Customer Firms (Left) and Industry of Supplier Firms (Right)

Note. This figure plots all SPLC relationships subject to S&P 500 universe. Manufacturing firm relationships are colored in green, wholesaler and retailer are colored in blue, transportation are colored in red, and other industries use other colors. The left figure uses customer firm's color, while right figure uses supplier firm's color. The width of the link comes from the log sales.

For logistics firms (NAICS code 42-49), we find 284 firms that fall into this sector. After price selection, 238 firms remain. We construct portfolios as above so that each quintile contains 47 firms. We note that all of the results in this section are presented with the first-digit NAICS classification of 3 and 4; in unreported tables, we replicate our findings at the two-digit level and find results that are qualitatively identical.

We do not examine other industries due to data limitation, i.e., other industries do not have enough firms to form quintile portfolios to test the statistic significance. Figure 2.2 shows the industry of the firm on both ends of the supply chain. For the customer map on the left, most of the links this time are blue and green, meaning manufacturing and logistic firms are the major customers in the whole economy. For the supply map on the right, most of the links are green, meaning only manufacturing firms are the major suppliers in the whole economy. Therefore, the manufacturing and logistics firm we analyzed are actually the most central sectors in the supply chain network.

2.3.1 Firm Characteristics Sorted by Centrality

In Table 2.1, we statistically verify that more central firms in manufacturing have lower stock returns than less central firms, while more central firms in logistics have higher stock returns than less central firms. We use eigenvector centrality for Table 2.1.

For the manufacturing industry, the lowest (value-weighted) quintile portfolio has an average monthly return of 1.77%, compared to only 1.07% per month for firms in the highest quintile, a statistically significant difference. The value-weighted portfolios are rebalanced monthly. We also present results based on equally-weighted portfolios, which again show a strong negative relationship between centrality and average returns. The economic magnitude of the relationship between centrality and average returns is substantial. For the value-weighted portfolios, the difference in returns between the highest and the lowest quintiles of eigenvector centrality is roughly -0.7% per month, or approximately -8.5% per year.

We examine other possible variables that may be related to centrality such as the size effect and the value effect. Using the log-scaled average size of firms in each quintile, we find a significant relationship between centrality and firm size. As eigenvector centrality increases, firm sizes are larger on average. For the value effect, however, the average ratio of book value to market value shows no salient trend as centrality increases.

For the logistics industry, the trend in average value-weighted returns as centrality increases seems to be opposite to that found in the manufacturing industry. We find statistical significance between two extreme quintile returns for the equal-weighted portfolios and observe an increasing relationship between centrality and average returns for both the value-weighted and the equal-weighted portfolios. Similar to the observations for manufacturing firms, firm sizes are larger as centrality increases, and no clear trend appears in the differences across quintiles for firm book-to-market ratios.

Table 2.1: Firm Characteristics Sorted by Eigenvector Centrality

	1(High)	2	3	4	5(Low)	High-Low	t-stat
Manufacturing (31-33)							
(Ave.) Eigenvector centrality 10^{-3}	2.316	0.733	0.410	0.207	0.087	2.229***	(16.04)
Value weighted returns %	1.07	1.25	1.59	1.53	1.77	-0.70*	(-1.97)
Equal weighted returns %	0.41	0.63	0.71	0.82	0.98	-0.57*	(-1.90)
Log(average size)	6.972	6.359	6.082	6.139	6.022	0.952***	(5.18)
Average BE/ME	0.477	0.552	0.553	0.488	0.471	0.006	(0.08)
Logistics (42-49)							
(Ave.) Eigenvector centrality 10^{-3}	2.189	0.511	0.257	0.137	0.067	2.122***	(8.88)
Value weighted returns %	2.03	1.54	1.74	1.53	1.50	0.53	(0.93)
Equal weighted returns %	1.67	1.87	1.27	1.68	1.01	0.66*	(1.93)
Log(average size)	6.871	6.299	6.291	6.119	6.152	0.719***	(3.77)
Average BE/ME	0.552	0.530	0.500	0.649	0.536	0.016	(0.20)

*p-value<10%, **p-value<5%, ***p-value<1%

Note. This table summarizes the firm characteristics across five quintiles of eigenvector centrality, including average value-weighted monthly returns, average equal-weighted monthly return, log-scaled average firm size, and average book-to-market ratio. For manufacturing, each portfolio has 143 firms. For logistics, each portfolio has 47 firms. The value-weighted portfolios are rebalanced monthly.

We use in-degree centrality for Table 2.2, which shows similar results to those in Table 2.2. We note that eigenvector centrality and in-degree centrality have, however, different foci. Since eigenvector centrality treats the network as undirected, it does not differentiate between suppliers and customers, but it captures the indirect information of how central a firm's linked partners are. Therefore, it gives more global information on a firm's centrality in the network. Since in-degree centrality omits customer information, it focuses on local supplier information. In-degree centrality also does not capture the indirect centrality information inherent in the firm's linked partners.

Table 2.2: Firm Characteristics Sorted by In-degree Centrality

	1(High)	2	3	4	1(Low)	High-Low	t-stat
Manufacturing (31-33)							
(Ave.) In-degree centrality	65.156	15.444	8.422	5.067	3.822	61.333***	(10.30)
Value weighted returns %	1.09	1.12	1.34	1.32	1.78	-0.70*	(-1.77)
Equal weighted returns %	0.67	0.96	0.87	0.87	1.22	-0.55*	(-2.06)
Log(Average Size)	7.194	6.512	6.231	5.962	5.928	1.266***	(8.32)
Average BE/ME	0.4386	0.4719	0.5116	0.5334	0.5145	-0.0759	(-0.95)
Logistics (42-49)							
(Ave.) In-degree centrality	68.037	17.259	9.444	5.3333	3.148	64.889***	(-7.01)
Value weighted returns %	1.67	1.67	1.55	1.52	1.34	0.33	(0.89)
Equal weighted returns %	1.98	1.56	1.39	1.29	1.37	0.61	(1.36)
Log(Average Size)	6.862	6.328	60402	6.079	6.253	0.610***	(3.24)
Average BE/ME	0.524	0.616	0.487	0.535	0.605	-0.081	(-0.93)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the firm characteristics across five quintiles of in-degree centrality, including average value-weighted monthly returns, average equal-weighted monthly return, log-scaled average firm size, and average book-to-market ratio. For manufacturing, each portfolio has 143 firms. For logistics, each portfolio has 47 firms. The value-weighted portfolios are rebalanced monthly.

Overall, from this analysis, we observe that average stock returns have a positive relationship with both eigenvector centrality and in-degree centrality for manufacturing, while this relationship is reversed for logistics firms. Given that common factors explain cross-sectional return variation, we additionally control for these factors in the subsequent factor regression tests.

2.3.2 Factor Regression Tests

While the above results show clear patterns in average returns based on network centrality, the pattern may be captured by existing factor models, such as the following CAPM and the four-factor model.

$$R_{it} - R_{ft} = \alpha_i + b_i \left(R_{mt} - R_{ft}\right) + \epsilon_{it}. \tag{2.3}$$

$$R_{it} - R_{ft} = \alpha_i + b_i \left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + u_i MOM_t + \epsilon_{it}. \tag{2.4}$$

It is reasonable to imagine that network characteristics may be related to these market-wide factors. For example, high returns associated with centrality may be explained by exposure to market-wide excess stock returns. Or, centrality could be related to SMB, the size factor, where central firms behave more like large firms than small firms. Correlations with HML, the value factor, and MOM, the momentum factor, may also reflect the concentration of suppliers and customers.

Table 2.3 presents estimates of the time-series factor regressions on five sorted value-weighted centrality portfolios for firms in manufacturing, using the eigenvector centrality measure. The estimates reveal a clear pattern of decreasing excess returns (alphas) as centrality increases. The alpha in the lowest centrality quintile is 0.51% in the CAPM model and 0.93% in the four-factor model. In the highest centrality portfolio, the alpha estimate is 0.24% in the CAPM model and 0.11% in the four-factor model. The alpha difference between the two extreme quintiles is 0.27% for CAPM and 0.82% for the four factor model. The differences in alphas between the highest and lowest centrality portfolios are again statistically significant and economically meaningful. The explanatory power of centrality for stock returns is then not diminished even after controlling for known factors related to firm size, leverage, and momentum.

Among the other factors, trends seem present within the SMB factor. For the size effect in the four-factor regression, the portfolio's exposure to small stocks becomes lower as centrality goes higher. The lowest centrality quintile shows a coefficient of 0.78 on SMB, compared to a coefficient of -0.35 for the highest centrality quintile. To further control for firm sizes, we perform double-sorting quintile portfolios based on both centrality and firm size. We first sort all firms into five quintiles based on their sizes, and then, for each quintile, we sort firms into five sub-quintiles based on their centralities. We then construct value-weighted portfolios in each sub-quintile. In Table 2.4, we find the same results that excess returns decrease as centrality increases for manufacturing firms.

No clear trend, however, appears for market premium, HML, and momentum since the loadings are not statistically different between centrality quintiles. This reinforces the point that known common risk factors do not explain the role of supply chain network centrality for firm returns.

Table 2.3: Factor Sensitivities by Eigenvector Centrality for Manufacturing Firms

N3 Portfolio	Factor Loadings α (%)	$R_{mt} - R_{ft}$	SMB	HML	MOM	$Adj.\ R^2$(%)
1(High)	0.235	0.888***				90.85
	(1.50)	(15.47)				
	0.114	0.894***	-0.347*	0.018	0.084	90.01
	(0.49)	(12.23)	(-2.07)	(0.119)	(1.025)	
2	0.295*	0.773***				88.74
	(1.78)	(13.79)				
	0.277	0.938***	-0.184	-0.453***	-0.061	93.77
	(1.34)	(14.28)	(-1.22)	(-3.29)	(-0.83)	
3	0.328	1.060***				92.78
	(1.33)	(17.60)				
	0.482*	0.953***	0.363*	-0.005	-0.008	93.04
	(1.86)	(11.63)	(1.93)	(-0.03)	(-0.09)	
4	0.356	1.256***				87.45
	(0.89)	(12.97)				
	0.571	1.087***	0.446	0.130	-0.142	87.82
	(1.36)	(8.22)	(1.47)	(0.47)	(-0.96)	
5(Low)	0.507	1.410***				85.54
	(1.55)	(11.96)				
	0.934*	1.157***	0.780**	-0.257	-0.132	87.53
	(1.95)	(7.63)	(2.24)	(-0.80)	(-0.78)	
High-Low	-0.272*	-0.522				
	(-1.72)	(-3.92)				
	-0.820*	-0.263	-1.127**	0.275	0.216	
	(-1.96)	(-1.28)	(-2.40)	(0.64)	(0.94)	

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table reports estimates of the Market Model (3) and the Fama-French model including a fourth momentum factor (4). Firms are chosen in the manufacturing industry sectors according to NAICS standard, including NAICS code 31-33. Portfolio returns are value-weighted firms returns formed for five quintiles of eigenvector centrality based on our supply chain data. Factor data are from Kenneth French's website. Observations are monthly returns from July 2011 to June 2013. 'High-Low' reports the difference between coefficient estimates from the first and the fifth centrality quintiles.

Table 2.4: 25 Portfolios Formed by Double-soring on Firm Size and Eigenvector Centrality for Manufacturing

N3				Firm Size						
Centrality	1(Large)	2	3	4	5(Small)	1(Large)	2	3	4	5(Small)
			CAPM α					$t\,(\alpha)$		
1(High)	0.207	-0.015	-1.423*	-0.874	-0.773	0.51	-0.02	-1.77	-1.22	-1.15
2	0.268	-0.082	-0.121	-0.730	0.148	0.94	-0.16	-0.26	-1.34	0.21
3	0.634**	0.005	-0.157	-0.008	-0.915	2.12	0.19	-0.35	-0.01	-1.21
4	0.561	0.050	0.445	-0.120	0.302	1.46	0.09	0.97	-0.14	0.50
5 (Low)	0.579*	0.911*	0.459	0.348	-0.415	1.72	1.74	1.35	0.66	-0.60
			Fama French & Momemtum factors α					$t\,(\alpha)$		
1(High)	0.047	-0.030	-0.298	-0.171	-0.131	0.16	-0.06	-0.58	-0.30	-0.21
2	0.348	0.608	0.181	-0.179	0.613	0.96	0.88	0.40	-0.41	0.96
3	0.356	0.547	0.363	0.692	-0.279	1.43	1.13	0.95	1.39	-0.39
4	0.829**	0.337	0.944**	0.721	0.664	2.09	0.58	2.30	0.98	1.03
5 (Low)	0.641*	1.106*	0.600	1.041**	0.029	1.81	1.90	1.66	2.69	0.05

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table reports 25 constant term α_i from the estimates of the Market Model (3) and the Fama-French model including a fourth momentum factor (4). The 25 portfolios are first sorted on sizes, then on eigenvector centrality. Portfolio returns are value-weighted. Firms are chosen in the manufacturing industry sectors according to NAICS standard, including NAICS code 31-33.

Table 2.5 presents estimates of the time-series factor regressions on five sorted value-weighted centrality portfolios for firms in logistics using the eigenvector centrality measure. Opposite to the results in Table 2.3 for manufacturing firms, the estimates reveal a clear pattern of increasing alphas as centrality increases. The alpha in the lowest centrality quintile is 0.76% in the CAPM model and 0.49% in the four-factor model. In the highest centrality portfolio, the alpha is 1.31% in the CAPM model and 1.43% in the four-factor model. The alpha difference between the two extreme quintiles is 0.56% for CAPM and 0.98% for the four-factor model. Other factors do not show statistically clear trends.

Tables 2.6 and 2.7 repeat the tests in Tables 2.3 and 2.5 using the in-degree centrality measure. The results are similar. Above all, the difference in alpha across extreme quintiles is statistically significant and economically important. This suggests that the standard pricing models do not explain all the cross-sectional variation in returns across centrality quintiles and that other factors related to network centrality might be included.

We also perform similar tests for other industries. In Tables 2.8 and 2.9, we find Mining (NAICS code 21), Utilities (NAICS code 22), and Construction (NAICS code 23) have the same eigenvector centrality result as observed for manufacturing firms (NAICS code 31-33). Comparing Table 15 with Table 2.3, we can see that mining, utilities, and construction earn significantly lower excess returns than manufacturing, as their alphas are all negative. This implies that firms in these industries are exposed to less residual systematic risk than manufacturing firms after controlling for common factors. Since mining, utilities, and construction are typically upstream industries compared to manufacturing, this evidence implies that upstream firms may be exposed to less systematic risk due to supply chain network structure. One possible reason for the difference here is that many manufacturing firms may have closer-to-linear supply chains with less diversification and higher systematic risks than firms with more connections. On the contrary, utilities, construction, and mining firms may be part of more networked chains, providing inputs to many other firms in different industries, which may mitigate risk exposure beyond the common factors. This observation supplements the empirical bullwhip effects such as those observed in Cachon et al. (2007) and Osadchiy et al. (2015).

For service industries (NAICS code 51-56), we do not find clear trends. As discussed in Section 3, this may be due to the data limitations, as service industries do not have the rich data structure present in manufacturing and logistics. For example, household consumption may be the primary customer segment for firms in Arts, Entertainment, and Recreation (NAICS code 71) or Accommodation and Food Service (NAICS code 72), but that segment is not captured in our data. It is also possible that other factors drive the pattern in the service industries. For example, financial ownership may be a more dominant factor than supply chain relationship for the Finance and Insurance Industry (NAICS code 52).

The abnormal returns we find may be compensation for both financial and operating risk. Since capital structure should be uncorrelated with firm returns in an efficient market, we argue that adding controls for leverage, such as using unlevered returns, would only change the multipliers of the factor model but not the significance of our results. We, therefore, conclude that the abnormal returns reflect that, in addition to the common factors, additional variation in systematic risk effects can be explained by supply chain network structure.

2.3.3 Robustness Test on Industry Concentration

Literature such as Hou and Robinson (2006) find that firm returns are related to industry concentration. The negative relationship for manufacturing firms and the positive relationship for logistics firms between centrality and returns could be influenced by other firm characteristics, such as greater concentrations of customer and supplier firms. Therefore, we further investigate whether the abnormal returns in manufacturing firms and logistics firms are relevant to their supplier or customer industry concentration, thus their supplier or customer industry competition. We measure industry j's concentration using the Herfindahl index, which is defined as

$$H_j = \sum_{i=1}^{I} s_{ij}^2,$$

where s_{ij} is the market share of firm i in industry j. Market share can be computed using revenue or market equity. Both measures are only imperfectly correlated with true market share. We use both revenue and the market capitalization to construct the Herfindahl indexes. For firm i's supplier / customer industry concentration, denoted by SH_i and CH_j respectively, we use sales weighted average Herfindahl index, which is defined (by ourselves) as

$$SH_i = \sum_{i=1}^{I} w_{ji} H_j, CH_i = \sum_{i=1}^{I} w_{ij} H_j$$

.

Similarly to the previous double-sorting method, we first sort all firms into five quintiles based on their supplier concentration or customer concentration; then, for each quintile, we sort firms into five sub-quintiles based on their centralities. In unreported tables, the trends in abnormal returns still hold, meaning that the second-order centrality effect is robust after controlling for supplier and customer industry concentration.

2.4 Summary and Directions

2.4.1 Summary of the Empirical Results

The main finding of this chapter concerns the second-order impact of a firm's network position, which explains part of its systematic risk. From the fundamental theory of idiosyncratic shock transmission leading to aggregate risks, we argue that the capability of risk diversification by incorporating more supply chain partners actually depends on the correlation of the idiosyncratic shocks. For manufacturing industries, firms can choose multiple less correlated partners to diversify idiosyncratic risks so that more central firms are exposed to less systematic risks and earn lower returns on average. For logistics industries, it may be difficult or costly for firms to hedge idiosyncratic risks from their partners, as their supply chain partners are more likely to be correlated due to geographical or industry proximity. As a result, more central firms in the logistics industries are exposed to higher systematic risks and thus earn higher returns on average. We also find that firms in mining, utilities, and construction industries share similar results to manufacturing firms while our limited data for service industries do not yield a clear pattern. Fundamentally different from the industry level results and underlying economic support from Ahern (2013), which argues more central industries earn higher expected returns monotonously, we find non-monotonous opposite systematic risk effects for firms in different industries.

Our results hold for both the eigenvector centrality measure and the in-degree centrality measure. We do not find significant results for out-degree centrality. This result implies that, from the systematic risk perspective, supplier relationships are more important than customer relationships. Other centrality measures including in-degree Herfindahl and out-degree Herfindahl are difficult to use due to our data limitations. In general, our finding improves on ex-post statistical measures of well known common risk factors and provides new evidence to support the view that firm-specific shocks may aggregate to form economy-wide volatility. It also demonstrates that firms' decisions on supply chain structure may form part of their economic fundamentals as an ex-ante determinant of systematic risk.

We suggest managers in different industries should adopt different supply chain strategies towards the control of systematic risk due to the nature of the industry. For manufacturing, our results reinforce the support for operational hedging of supply, such as the form used by Nokia, although managers should also be aware that decreasing exposures to systematic risk in this way can also lead to lower future long-term average returns. For logistics, our results

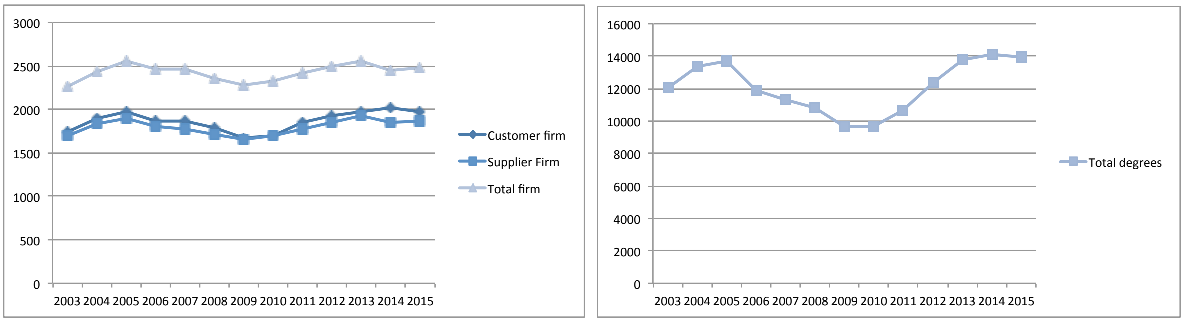


Figure 2.3: Time Series Supply Chain Data (Left: Number of Firms, Right: Number of Relationships).

suggest that operational hedging may be costly.

2.4.2 Empirical Extensions

Besides supply chain data from Bloomberg, other data vendors such as FactSet Revere also provide coverage on firm supply chain. Cross-sectionally, FactSet does not provide information as detailed as Bloomberg. As for most supply chains, FactSet only keeps track the existence of such a relationship, without quantified information such as the sales on the link. However, FactSet has time series information while Bloomberg does not. In this subsection, we discuss some time-series features of FactSet data and propose some directions for continuing work.

The number of firms and the number of supply chain relationships are shown in Figure 2.3. Both numbers decreased during the 2008 crisis but have steadily increased thereafter. Also, the number of links dropped more than the number of firms. To make this clearer, we draw the supply chain networks using the similar force-directed algorithm and color the most eigenvector central firms red, and the least eigenvector central firms blue, as shown in Figure 2.4.

The core points colored in red are the most eigenvector central firms, while the periphery points colored in blue are the least central firms. From the position of the points, we can see

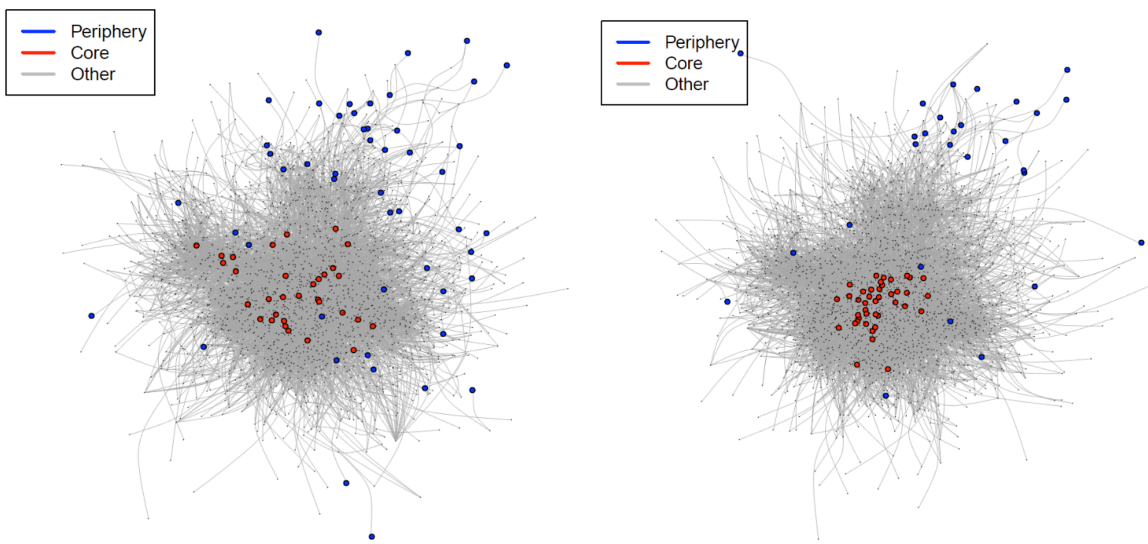


Figure 2.4: Most Central and Least Central firms in Supply Chain Network (Left: As of June 2007, Right: As of July 2009).

that the economic activity of June 2009 are more concentrated among a few well connected firms than that of July 2007. This observation is interesting as it captures some systematic risk implication not explained by the commonly studied sector network. Note that in the sector network, the existence of industry-to-industry supply chains do not change between those two periods, meaning that if one industry sector supports input to another industry sector in 2007, the relationship still holds for 2009. Therefore, the fact that only the firm-to-firm supply chain relationships disappear is worth studied as it can explain additional systematic risk which the industry network cannot account for.

The next empirical experiment we run on the time series supply chain networks is to check the risk implication of the key position for the supply chain network flows, i.e. the so-called "chokepoint". We define these points in a way that if they are removed, the directed shortest distance between suppliers and customers would be greatly increased. In another word, in the directed graph of supply chain networks, it is most likely the network flow will bypass such points. Therefore, these points are with systematic importance as they serve as major venues for economic activities. During the crisis, the firms at those positions are likely to be

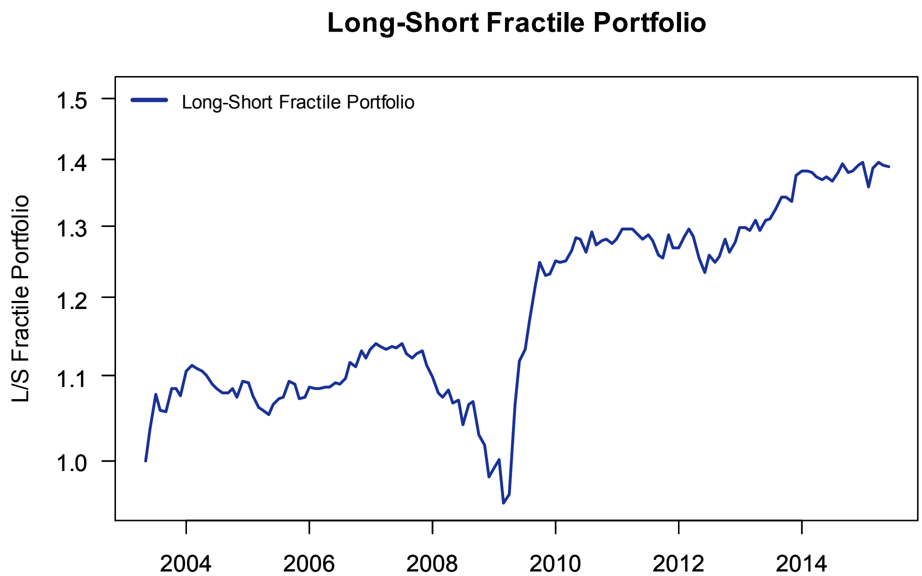


Figure 2.5: Systemic Implication of Chokepoint Firms

The portfolio is formed by taking a long position in the highest number of shortest-path firms and a short position in the smallest number of shortest-path firms. It performs better than the market in the long term, albeit with a big draw down during the 2008 crisis and a quick recovery afterwards.

hit the worst as they aggregate all the negative shocks on the supply chain network flows. However, during the expansion period, the firms at those positions are likely to recover the fastest as they aggregate all the increase in network flows. Since those positions have more exposure to systematic risk, we also expect them to have higher expected reward, i.e. to outperform other firms in the long run.

To test the above reasoning, similar as the long-short strategy in Chapter 1, we construct another long-short strategy on the chokepoint firms by longing the top quintile and shorting the bottom quintile of firms ranked by their chokepoint scores. The result is shown in Figure 2.5. As expected, the chokepoints out-perform during booming time such as 2009-2010 periods, while under-perform during the crisis, i.e. 2008-2009 period. They also have higher expected returns in the long run, suggesting the chokepoint firms have higher systematic risk exposure due to their network positions.

2.4.3 Theoretical Discussion on Systematic Risk

Previous literature study the supply chain network systematic risk from the sector level only. Among which Lucas (1977) argues that microeconomic shocks would average out at the aggregated level proportional to $\frac{1}{\sqrt{n}}$, where n is the number of economic entities, due to the Law of Large Numbers. Recently, Acemoglu et al. (2012) models input-output linkages and suggests Lucas (1977) only holds under symmetric network structure, and microeconomic shocks may lead to aggregated fluctuations if the network topology is asymmetric. In modeling firm-level supply chain networks, there are still several considerations missing in the existent theoretical literature.

First, the firm level connections are overlooked in the sector level networks. As we see from Figure 2.3, the density of firm level connections decreases during the recession while it increases during the expansion period. The systematic risk implication is not captured by sector level networks. Second, both firm and sector level shocks may be correlated together, which would lead to aggregated risk. In this subsection, we build a firm-level supply chain network model using a two-level production function capturing the missing parts. The systematic risk is thus the volatility of the aggregate total production in the network.

There are three major streams of literature on network theory study, i.e. 1) production networks, 2) social networks, and 3) financial networks. Among all the literature, the general unified modeling framework has some clear similarity. Given n agents (persons in social networks, firms or industries in production networks, or banks in financial networks), other agents influence the state of agent i, x_i, through the network connections of linear relationships: $x_i = f\left(\sum_{i=1}^{n} w_{ij} x_j + \epsilon_i\right)$, where $w_{ij} \geq 0$ is the element in the weighting matrix capturing the strength of the interaction, ϵ_i is the shock term. The linear relationship allows analytical tractability.

Specifically, on production networks, Acemoglu et al. (2012) use Cobb-Douglas production function for the network connections $X_i = z_i \left(l_i\right)^{\alpha} \prod_{j=1}^{n} X_{ij}^{(1-\alpha)w_{ij}}$ in their study on production network. The log output is $x_i = logz_i + \alpha logl_i + (1-\alpha)\sum_{j=1}^{n} w_{ij}x_{ij} = f\left(\sum_j^n w_{ij}x_j\right)$ which is linear. The log GDP is $y = \frac{1}{n}\sum_{i=1}^{n} x_i$. Bimpikis et al. (2015) use a linear production technology for the network connections that $x_i = \sum_{j=1}^{n} w_{ij}x_{ij}$ with diseconomies of scale assumption for further tracktability.

On social networks, traditional literature such as Jackson and Wolinsky (1996) use an explicit linear function $f\left(\sum_j^n w_{ij}x_j\right)$ to model network interactions. Recent literature models the utility functions with quadratic terms embedded by linear relationships of network connections. Candogan et al. (2012) model local consumption externalities in agent utility using a linear relationships of adjacent networks $u_i = a_i x_i - b_i x_i^2 + x_i \sum_{j=1}^{n} w_{ij}x_j - p_i x_i = f\left(x_i, \sum_{j=1}^{n} w_{ij}x_j\right)$.

On financial networks, the focus is usually on the market value of a bank or its ability to repay its obligations. Elliott and Hazell (2015) models the value of a bank as the sum of its own asset and cross-holdings of other banks $x_i = p_i + \sum_{j=1}^{n} w_{ij}x_j = f\left(\sum_{j=1}^{n} w_{ij}x_j\right)$, a linear relationships of network connections. Acemoglu et al. (2015b) models the bank's ability to repay its debt and the payment is $x_i = max\left\{min\left\{\sum_j^n w_{ij}x_j + a + \epsilon_i, \xi\right\}, 0\right\} = f\left(\sum_j^n w_{ij}x_j\right)$.

The model we build here is similar to that in Acemoglu et al. (2012). Suppose that there are n industry sectors, denoted by the set S_1, S_2, ..., and S_n. Suppose that individual firms in the same industry sector have the same Cobb-Douglas production function with constant returns to scale, subject to firm-level idiosyncratic shocks. Firms in the same industry sector produce the exact same products which are perfectly substitutable. Firms can only source from and sell to other firms with which they have established supply chain relationships.

Define output from firm l in sector j that serves as input to firm k in sector i as x_{ij}^{kl}. The production from sector j to sector i is $x_{ij} = \sum_{k\in S_i}\sum_{l\in S_j} x_{ij}^{kl}$. Define output from firm k in sector i as x_i^k. Sector i's total production is $x_i = \sum_{k\in S_i} x_i^k$.

Suppose we have a unit labor in the economy allocating to each sector (l_i) and to each firm (l_i^k), i.e. $\sum_{i=1}^n l_i = 1$, where $l_i = \sum_{k\in S_i} l_i^k$. The unit labor here is also the owner of firms and the consumer. Suppose consumption good produced by firm k in sector i is c_i^k, and by sector i is $c_i = \sum_{k\in S_i} c_i^k$. The aggregate output measured by total consumption should equal to labor wage h.

We define a competitive equilibrium of this economy with n sectors consisting of prices $(p_i, i \in \{1, ..., n\})$, wage h, consumption bundle $\left(c_i = \sum_{k\in S_i} c_i^k, i \in \{1, ..., n\}, k \in S_i\right)$, and quantities $\left(l_i^k, x_i^k, x_{ij}^{kl}, \forall i, j, k, l\right)$ such that

1. the representative consumer solves the problem to maximize her utility;

2. the firms in each sector solve the problem to maximize their profits, which are 0 in expectation for a competitive equilibrium;

3. while the labor and good markets clear at both the firm level and the sector level, i.e. for any firm k in any sector i, $x_i^k = c_i^k + \sum_{j=1}^n \sum_{l\in S_j} x_{ji}^{lk}$ and $\sum_{k\in S_i} l_i^k = l_i$; for any sector i, $x_i = c_i + \sum_{j=1}^n x_{ji}$ and $\sum_{i=1}^n l_i = 1$.

The consumer problem requires diversifying the consumption over all sectors under the budget, i.e. $max\ u(c_1, c_2, ..., c_n) = A\Pi_{i=1}^n (c_i)^{\frac{1}{n}}$, such that $\sum_{i=1}^n p_i c_i \le h$. First order condition (FOC) yields for optimal consumption level $c_i = \frac{h}{np_i}$.

The firm problem solves the following maximization problem:

$$max\Pi_i^k = p_i x_i^k - hl_i^k - \sum_{j=1}^n p_j \sum_{l\in S_j} x_{ij}^{kl}$$

subject to the Cobb-Douglas technologies below with constant returns to scale.

$$x_i^k = z_i^k \left(l_i^k\right)^\alpha \prod_{j=1}^n \left(\sum_{l\in S_j} x_{ij}^{kl}\right)^{(1-\alpha)w_{ij}}$$

where $w_{ij} \ge 0$ is the element in the weighting matrix capturing the elasticity of each sector's input, or the strength of the sector interaction. $\sum_{j=1}^n w_{ij} = 1$.

Taking FOC with respect to l_i^k, $\frac{\partial \Pi_i^k}{\partial l_i^k}$ yields $\frac{\alpha p_i x_i^k}{l_i^k} - h = 0 \implies l_i^k = \frac{\alpha p_i x_i^k}{h}$.

Taking FOC with respect to x_{ij}^{kl}, $\frac{\partial \Pi_i^k}{\partial x_{ij}^{kl}}$ yields $\frac{(1-\alpha) w_{ij} p_i x_i^k}{\sum_{l \in S_j} x_{ij}^{kl}} - p_j = 0 \implies \sum_{l \in S_j} x_{ij}^{kl} = \frac{(1-\alpha) w_{ij} p_i x_i^k}{p_j}$.

The sector input-output is thus $x_{ij} = \sum_{k \in S_i} \sum_{l \in S_j} x_{ij}^{kl} = \frac{(1-\alpha) w_{ij} p_i x_i}{p_j}$.

Because we have perfect competition within sectors, meaning firms operating in a same sector face the same input prices, they will choose the same proportions of inputs from other sectors (including labor). We write this as

$$\sum_{l \in S_j} x_{ij}^{kl} = \gamma_i^k x_{ij}, l_i^k = \gamma_i^k l_i$$

This means $\gamma_i^k = \frac{\sum_{l \in S_j} x_{ij}^{kl}}{x_{ij}} = \frac{l_i^k}{l_i}$ and $\sum_{k \in S_i} \gamma_i^k = 1$.

Therefore, the production from firm i in sector k becomes $x_i^k = z_i^k \gamma_i^k (l_i)^\alpha \prod_{j=1}^n (x_{ij})^{(1-\alpha) w_{ij}}$, while the production from sector i is the following:

$$x_i = z_i (l_i)^\alpha \prod_{j=1}^n (x_{ij})^{(1-\alpha) w_{ij}}$$

where $z_i = \sum_{k \in S_i} \gamma_i^k z_i^k$.

Proposition 2.4.1. *The sector productivity shock is a sum of firm level shocks, weighted by each firm's sector share, i.e.* $z_i = \sum_{k \in S_i} \gamma_i^k z_i^k$. *Firm-level supply chain connections determine the shape of the sector shock distribution.*

Using the sector shock representation, substituting FOCs into the production function of a firm in sector i, we have

$$\alpha lnh = \epsilon_i + B + lnp_i - (1-\alpha) \sum_{j=1}^n w_{ij} lnp_j + (1-\alpha) \sum_{j=1}^n w_{ij} lnw_{ij}$$

where $\epsilon_i = lnz_i$, $B = \alpha ln\alpha + (1-\alpha) ln(1-\alpha)$,

Define the influence vector as $v^{'} = \frac{\alpha}{n} 1^{'} \left[I - (1-\alpha) W\right]^{-1}$ satisfying $\sum_{i=1}^{n} v_i = 1$[4], and multiply the above equation by the ith element of v and sum over all sectors[5]. We then have

$$lnh = v^{'}\epsilon + \mu, \mu = \frac{B}{\alpha} + \frac{1}{n}\sum_{i=1}^{n} lnp_i + \frac{1-\alpha}{\alpha}\sum_{i=1}^{n} v_i \sum_{j=1}^{n} w_{ij} lnw_{ij}$$

Now set $lnA = lnn - \frac{B}{\alpha} + \frac{1-\alpha}{\alpha}\sum_{i=1}^{n} v_i \sum_{j=1}^{n} w_{ij} lnw_{ij}$, and normalize the price index to 1, i.e. $\frac{n}{A}\left(\prod_{i=1}^{n} p_i\right)^{\frac{1}{n}} = 1$, then we have $\frac{B}{\alpha} + \frac{1}{n}\sum_{i=1}^{n} lnp_i + \frac{1-\alpha}{\alpha}\sum_{i=1}^{n} v_i \sum_{j=1}^{n} w_{ij} lnw_{ij} = 0$. The aggregate output, or the GDP, is the influence vector weighted sum of sector-specific productivity shocks below.

$$y = lnh = v^{'}\epsilon$$

The volatility of the aggregate output GDP, or the systematic risk is

$$Var\left[y\right] = Var\left[v^{'}\epsilon\right]$$

where ϵ is a column vector with $\epsilon_i = lnz_i = ln\left(\sum_{k\in S_i} z_i^k \gamma_i^k\right)$.

Comments on Firm Supply Chain Connections

Since the sector shock is a sum of firm level shocks weighted by each firm's sector share, firm-level connections affect the sector shock through the ex-post distribution of a firm's sector share γ_i^k.

While the supply chain connections may be the same at the sector-level, the connection density can be quite different at the firm level. For example, in Figure 2.6, the left case has very sparse connections between the firm in two different sectors (e.g. during crisis such

4. This is because $v^{'}\left[I-(1-\alpha)W\right]1 = \frac{\alpha}{n}1^{'}\cdot 1 = \alpha \implies \sum_{i=1}^{n} v_i - (1-\alpha)\sum_{i=1}^{n} v_i = \alpha \implies \sum_{i=1}^{n} v_i = 1$.

5. The ith element of v is essentially $v_i = \frac{p_i x_i}{\sum_{j=1}^{n} p_j x_j}$. Proof is omitted here.

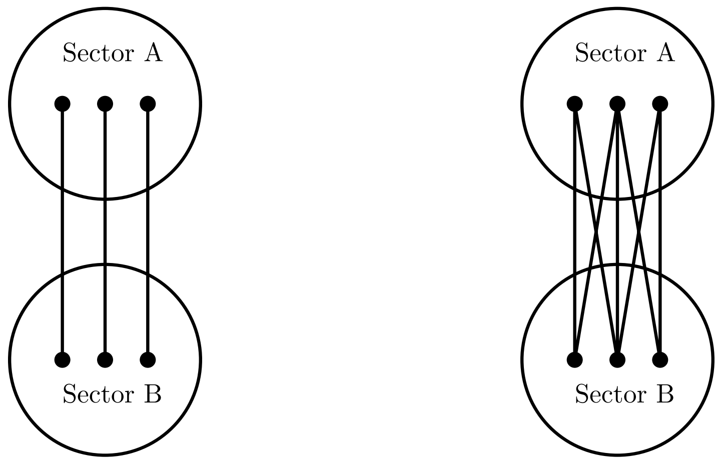


Figure 2.6: Firm-level Supply Chain Connections (Left: Sparse Connections, Right: Dense Connections)

as 2009), while the right case has very dense connections (e.g. during normal time such as 2007). Ex-post shock realized, the firm's sector share γ_i^k in the left case would have heavier tails on the distribution than the right case because the input from the other sector are more volatile.

When firms form supply chain connections ex-ante, the input supply curve faced by an individual firm is horizontal, perfectly elastic, and does not depend on firm-level connections, or the firm level shocks. However, it would become upward sloping ex-post shock realization. Firms with less connections to suppliers not only face an upward sloping input curve, but also become more sensitive to the supplier shocks.

In the case when firm-level connections are sparse and the suppliers are not as productive as the subject firm, the firm has to either pay excessive price or buy less input than the firm would ideally have wanted. In other words, it is possible to have a highly productive firm who is stuck with a set of unproductive suppliers and must pay higher prices or get less sector market share. This mismatch creates distortion on the firm's sector share γ_i^k because it limits the capacity of the productive firms. The less firm-level connections, the more likely this will happen, the higher variance the distribution of γ_i^k would be.

At the sector shock level, the more volatile the distribution of γ_i^k, the higher the variance of the aggregated sector shock z_i, thus the higher the systematic risk, $Var\left[v^{'}\epsilon\right]$, ceteris paribus.

Since the production function is concave, following Proposition 4 in Acemoglu et al. (2015a), the expected aggregated output $E[y]$ decreases when $Var\left[v^{'}\epsilon\right]$ increases, i.e. the sparsely connected supply chain network would have less total production in expectation. This is exactly the case for the 2008-2009 crisis, when firms lost many supply chain relationships and the output demand was low. During normal economic environment, it is more likely that firms form dense supply chain networks to have more production in expectation to meet high demand, such as the empirical evidence shown in Figure 2.3.

Proposition 2.4.2. *For concave production functions, a sparse firm-level supply chain network results in less total output than a dense firm-level supply chain network in expectation.*

To justify the above analysis, we run a simulation to illustrate the insight, based on the two-level production function and the supply chain network structure introduced above. There are two steps in the economy[6].

Step 1 (Relationship-formation): Each firm chooses a set of suppliers to contract for intermediate input. Ex-ante the firms make 0 profit, and the market is perfectly competitive.

Step 2 (Input-acquisition): Each firm draws i.i.d. production shock. Ex-post the input supply curve is upward sloping. Input quantity depends on the supplier actual production.

The distribution of γ_i^k is shown in Figure 2.7. In the first case, each firms connect to 80% of suppliers in another sector. In the second case, each firms connect to only 2% of suppliers in another sector. The first case, of which the firm-level connections are dense, has a standard deviation of 0.0001. While in the second case, of which the firm-level connections are sparse, has a standard deviation of 0.0023. It is clear that the first case has a much less volatile distribution of sector weights. As a result, the simulation also shows that the dense

6. Each sectors have 100 firms. The input elasticity is set as 0.3 for labor and 0.7 for intermediate inputs.

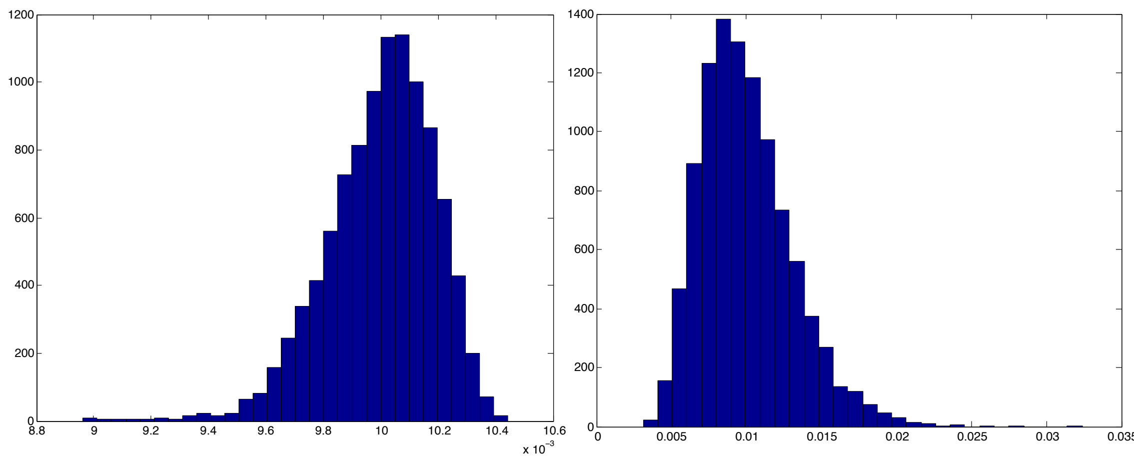


Figure 2.7: Simulation of Sector Weight γ_i^k (Left: Firms Connect to 80% of Suppliers, Right: Firms Connect to 2% of Suppliers).

connection case has approximately 3.67% more total output than the sparse connection case. This is because with more firm-level connections, it is more likely for firms to get sufficient input due to the diversification of the supplier base.

The distribution of the sector weights against the normal distribution, i.e. the quantile-quantile (QQ) plot, is shown in Figure 2.8. Both cases exhibit sizable and systematic deviations from the normal distribution. Case 1 shows a heavier left tail while case 2 shows a heavier right tail. In unreported results, we find that only the sector weight with modest density of firm-level connections may be approximately normal distributed.

Proposition 2.4.3. *With firm-level supply chain connection variation, there is no guarantee that the firm-level production output is normally distributed.*

Thus, in general, the standard deviation of sector weight is not a sufficient statistics for firm output variations.

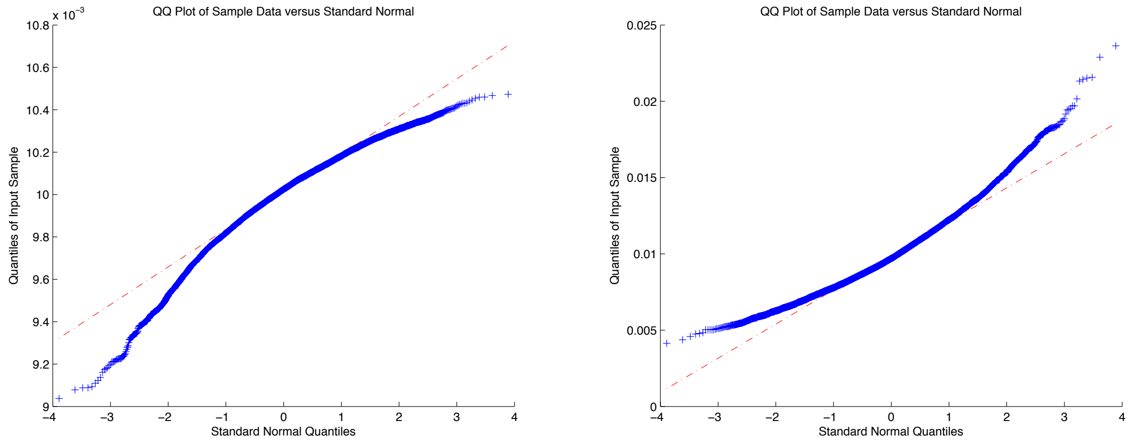


Figure 2.8: Q-Q Plot of the Sector Weight γ_i^k against the Normal Distribution (Left: Firms Connect to 80% of Suppliers, Right: Firms Connect to 2% of Suppliers).

Comments on Sector Supply Chain Connections

There are several scenarios which can lead to aggregated volatility asymptotically, i.e. $Var\left[v'\epsilon\right] \neq 0$ when $n \to \infty$.

First, as shown in Acemoglu et al. (2012), when there is a sector playing asymmetric position in the supply chain network, there can be systematic aggregated fluctuation in outputs. For example, a star network where one sector supplies all other sectors:

$$w = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{bmatrix} \quad \Longrightarrow \; v = \frac{\alpha}{n}1' \left[I - (1-\alpha) W\right]^{-1} = \left[\frac{\alpha}{n} + (1-\alpha), \frac{\alpha}{n}, \cdots, \frac{\alpha}{n}\right]$$

$$\Longrightarrow \; Var\left[logGDP\right] = \|v\|^2 \sigma^2 \to (1-\alpha)\,\sigma^2$$

Second, when there is some degree of correlation between the sectors, there can be systematic aggregated fluctuation. For example, assuming there is a correlation of ρ between any two sectors in a ring network structure:

$$w = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \implies v = \left[\frac{1}{n}, \frac{1}{n}, \cdots, \frac{1}{n}\right]$$

$$\implies Var\left[logGDP\right] = n \cdot \frac{1}{n^2} \cdot \sigma^2 + \frac{n\left(n-1\right)}{n^2} \cdot \rho\sigma^2 \rightarrow \rho\sigma^2$$

To sum up, in supply chain networks, the sector network topology based on the sector adjacent weighting matrix, which is mostly commonly studied in the economic network literature, is only one factor that matters for systematic risk. Shock correlation and the production technology, capturing input complementarity and substitutability, also matter.

Table 2.5: Factor Sensitivities by Eigenvector Centrality for Logistics Firms

N4		Factor Loadings				
Portfolio	Alpha(%)	$R_{mt} - R_{ft}$	SMB	HML	MOM	*Adj.* R^2(%)
1(High)	1.314***	0.747***				84.93
	(3.26)	(7.62)				
	1.428***	0.768***	0.006	-0.589	0.024	86.43
	(3.44)	(5.85)	(0.02)	(-2.14)	(-0.16)	
2	0.894***	0.671***				70.41
	(3.78)	(11.67)				
	0.916***	0.976***	0.034	-0.502	0.031	72.32
	(2.41)	(8.13)	(0.13)	(-1.99)	(0.23)	
3	0.812**	0.964***				83.05
	(2.23)	(10.89)				
	0.801**	0.758***	-0.140	-0.152	0.164	83.75
	(3.36)	(10.03)	(-0.81)	(-0.96)	(1.93)	
4	0.708**	0.857***				86.41
	(2.50)	(12.40)				
	0.669**	0.916***	-0.171	-0.190	0.019	85.49
	(2.14)	(9.26)	(-0.75)	(-0.92)	(0.17)	
5(Low)	0.759	0.776***				69.60
	(1.44)	(6.03)				
	0.485	0.942***	-0.548	0.141	0.048	67.70
	(0.84)	(5.17)	(-1.31)	(0.37)	(0.23)	
High-Low	0.556	-0.029				
	(1.53)	(-0.20)				
	0.975*	-0.175	0.553	-0.730	-0.024	
	(1.93)	(-0.90)	(1.24)	(-1.69)	(-0.11)	

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table reports estimates of the Market Model (3) and the Fama-French model including a fourth momentum factor (4). Portfolio returns are value-weighted. Firms are chosen in the logistics industry sectors according to NAICS standard, including wholesale trade (NAICS code 42), retail trade (NAICS code 44-45), Transportation & Warehousing (NAICS code 48-49). Portfolio returns are value-weighted firms returns formed for five quintiles of eigenvector centrality based on our supply chain data. Factor data are from Kenneth French's website. Observations are monthly returns from July 2011 to June 2013. Stocks with a price less than five dollars are excluded to avoid liquidity effect. 'High-Low' reports the difference between coefficient estimates from the first and the fifth centrality quintiles.

Table 2.6: Factor Sensitivities by In-degree Centrality for Manufacturing Firms

N3 Portfolio	Factor Loadings α (%)	$R_{mt} - R_{ft}$	SMB	HML	MOM	$Adj.\ R^2(\%)$
1(High)	0.100	1.274***				84.32
	(0.21)	(11.41)				
	0.260	0.895***	-0.297*	-0.298*	-0.029	91.64
	(1.18)	(12.86)	(-1.87)	(-2.04)	(-0.37)	
2	0.309	0.808***				89.73
	(1.35)	(14.51)				
	0.234	1.104***	-0.054	-0.310*	0.028	92.92
	(0.89)	(13.20)	(-0.28)	(-1.77)	(0.30)	
3	0.204	1.073***				92.92
	(0.82)	(17.64)				
	0.401	1.021***	0.236	0.106	-0.205*	91.66
	(1.30)	(10.42)	(1.05)	(0.52)	(-1.87)	
4	0.243	1.146***				90.82
	(0.80)	(15.45)				
	0.476	0.942***	0.101	-0.369	-0.040	87.12
	(1.03)	(8.94)	(0.42)	(-1.67)	(-0.34)	
5(Low)	0.851**	0.972***				87.04
	(2.72)	(12.73)				
	0.984***	1.083***	0.558	-0.398	-0.160	86.03
	(2.96)	(7.41)	(1.67)	(-1.30)	(-0.97)	
High-Low	-0.751*	0.302**				
	(-1.73)	(2.70)				
	-0.724*	-0.188	-0.855*	0.100	0.130	
	(-1.79)	(-1.01)	(-2.01)	(0.26)	(0.63)	

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table reports estimates of the Market Model (3) and the Fama-French model including a fourth momentum factor (4). Firms are chosen in the manufacturing industry sectors according to NAICS standard, including NAICS code 31-33. Portfolio returns are value-weighted firms returns formed for five quintiles of indegree centrality based on our supply chain data. Factor data are from Kenneth French's website. Observations are monthly returns from July 2011 to June 2013. 'High-Low' reports the difference between coefficient estimates from the first and the fifth centrality quintiles.

Table 2.7: Factor Sensitivities by In-degree Centrality for Logistics Firms

N4		Factor Loadings				
Portfolio	Alpha(%)	$R_{mt} - R_{ft}$	SMB	HML	MOM	$Adj.\ R^2(\%)$
1(High)	1.137***	0.553***				76.05
	(4.40)	(8.79)				
	1.02***	0.677***	-0.277	-0.245	0.143	80.04
	(4.04)	(8.50)	(-1.52)	(-1.47)	(1.61)	
2	0.828*	0.882***				85.01
	(2.06)	(9.00)				
	0.738*	0.963***	0.521*	-0.390	0.091	86.58
	(1.93)	(7.97)	(1.88)	(-1.54)	(0.67)	
3	0.577	1.015***				80.11
	(1.37)	(9.88)				
	0.495	1.104***	-0.178	-0.198	0.123	78.54
	(1.06)	(7.47)	(-0.52)	(-0.64)	(0.75)	
4	0.480	1.079***				76.91
	(1.27)	(11.71)				
	0.541	1.054***	-0.520	0.150	0.102	77.81
	(1.29)	(7.92)	(-1.71)	(0.54)	(0.68)	
5(Low)	0.339	1.046***				75.62
	(0.69)	(8.69)				
	0.054	1.221***	-0.496	0.131	0.135	75.11
	(0.10)	(7.24)	(-1.28)	(0.37)	(0.71)	
High-Low	0.798*	-0.493***				
	(1.92)	(-4.13)				
	0.962*	-0.544***	0.544	-0.646	0.096	
	(2.07)	(-3.17)	(0.56)	(-1.04)	(0.04)	

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table reports estimates of the Market Model (3) and the Fama-French model including a fourth momentum factor (4). Portfolio returns are value-weighted. Firms are chosen in the logistics industry sectors according to NAICS standard, including wholesale trade (NAICS code 42), retail trade (NAICS code 44-45), Transportation & Warehousing (NAICS code 48-49). Portfolio returns are value-weighted firms returns formed for five quintiles of indegree centrality based on our supply chain data. Factor data are from Kenneth French's website. Observations are monthly returns from July 2011 to June 2013. Stocks with a price less than five dollars are excluded to avoid liquidity effect. 'High-Low' reports the difference between coefficient estimates from the first and the fifth centrality quintiles.

Table 2.8: Firm Characteristics Sorted by Eigenvector Centrality (NAICS 21-23)

	1(High)	2	3	4	5(Low)	High-Low	t-stat
NAICS code (21-23)							
(Ave.) Eigenvector centrality 10^{-3}	0.266	0.082	0.047	0.027	0.006	0.260***	11.31
Value weighted returns %	0.49	0.69	0.85	1.01	1.10	-0.62	-1.49
Equal weighted returns %	0.11	0.32	0.78	0.76	0.86	-0.75*	1.79
Log(average size)	6.921	6.730	6.350	6.550	6.233	0.688***	4.08
Average BE/ME	0.614	0.756	0.694	0.597	0.551	0.062	1.06

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the firm characteristics across five quintiles of eigenvector centrality, including average value-weighted monthly returns, average equal-weighted monthly return, log-scaled average firm size, and average book-to-market ratio. Each portfolio has 31 firms. The value-weighted portfolios are rebalanced monthly.

Table 2.9: Factor Sensitivities by Eigenvector Centrality for Mining, Utilities and Construction Firms

N2		Factor Loadings				
Portfolio	α (%)	$R_{mt} - R_{ft}$	SMB	HML	MOM	$Adj.\ R^2$(%)
1(High)	-1.153*	1.399***				79.54
	(-1.74)	(9.09)				
	-1.179	1.458***	-0.091	-0.330	0.114	76.83
	(-1.52)	(5.80)	(-0.15)	(-0.68)	(0.45)	
2	-0.897	1.512***				79.42
	(-1.25)	(9.06)				
	-1.023	1.583***	-0.329	0.092	-0.103	76.28
	(-1.21)	(5.76)	(-0.48)	(0.17)	(-0.37)	
3	-0.346	0.762***				61.90
	(-0.62)	(5.93)				
	-0.680	0.935***	-0.458	0.262	0.155	59.96
	(-1.09)	(4.63)	(-0.92)	(0.67)	(0.76)	
4	-0.374	1.129***				72.88
	(-0.58)	(7.58)				
	-0.598	1.213***	-0.071	-0.376	0.261	71.72
	(-0.83)	(5.20)	(-0.12)	(-0.84)	(1.11)	
5(Low)	-0.479	1.339***				78.22
	(-0.72)	(8.74)				
	-0.626	1.456***	-0.201	-0.215	0.221	75.94
	(-0.82)	(5.90)	(-0.33)	(-0.45)	(0.89)	
High-Low	-0.674*	0.060				
	(-1.95)	(1.25)				
	-0.553	0.002	0.110	-0.115	-0.107	
	(-1.51)	(0.02)	(0.51)	(-0.68)	(-1.20)	

*p-value<10%, **p-value<5%, ***p-value<1% *Notes.* This table reports estimates of the Market Model and the Fama-French model including a fourth momentum factor. Portfolio returns are value-weighted. Firms are chosen in the NAICS standard starting with first digit "2", including Mining (NAICS code 21), Utilities (NAICS code 22) and Construction (NAICS code 23). Portfolio returns are value-weighted firms returns formed for five quintiles of eigenvector centrality based on our supply chain data. Factor data are from Kenneth French's website. Observations are monthly returns from July 2011 to June 2013. 'High-Low' reports the difference between coefficient estimates from the first and the fifth centrality quintiles.

CHAPTER 3

SOURCING WITH FINANCING IN SUPPLY CHAINS

Two innovative financing schemes have emerged in recent years that were intended to enable suppliers to obtain financing for production. The first scheme is known as *Purchase Order Financing* (POF), under which financial institutions offer loans to suppliers by considering the value of purchase orders issued by reputable manufacturers. The second scheme is known as *Buyer Direct Financing* (BDF), under which manufacturers issue sourcing contracts *and* loans directly to their suppliers. Both schemes are closely related to the supplier's performance risk because the repayment of these loans hinges upon successful delivery by the supplier. In this chapter, we use a game-theoretical model to capture the interactions between three parties (a manufacturer, a supplier who can exert unobservable effort to improve delivery reliability, and a bank) so that we can examine the relative efficiency of these two schemes. When the manufacturer and the bank have symmetric information, we find that from the manufacturer's perspective, both POF and BDF yield the same payoff, even though BDF allows the manufacturer more flexibility in selecting financing terms. However, when the manufacturer has superior information about the supplier, we find that information asymmetry only lowers the efficiency of POF when the supplier's asset level is sufficiedntly low. In addition, BDF is relatively more efficient than POF when the supply market contains a large proportion of inefficient suppliers, when the difference in efficiency between suppliers is great, or when the manufacturer's alternative sourcing option is expensive.

3.1 Introduction

To reduce production costs, many manufacturers, retailers, and intermediaries source products from small suppliers (contract manufacturers), who are often located in developing countries. With a lack of access to public debt or equity markets, these suppliers often rely on two channels for external financing. The first channel is asset-based loans offered by banks and secured by suppliers' physical assets, such as inventories and equipment Buzacott and Zhang (2004). The second is factoring, under which suppliers sell account receivables to financial institutions at a discount for immediate cash payment Klapper (2006); Sodhi and Tang (2012). However, both channels require suppliers to have certain tangible internal resources, which may not be readily available. Consequently, many new suppliers fail to secure the financing to begin production after landing a profitable, yet over-large, purchase order from a reputable buyer Tice (2010). Similarly, with balance sheets weakened by the recent financial crisis and many institutions still recovering, even established suppliers may fail to secure sufficient financing to meet increasing orders from buyers Martin (2010). Inevitably, suppliers' difficulties obtaining financing affect manufacturers adversely when the latter are left with more expensive sourcing options or, even worse, fail to deliver end products to consumers.

To meet the financing needs of the aforementioned suppliers, two innovative schemes have recently emerged. The first is known as the *Purchase Order Financing* (POF), under which financial institutions lend to suppliers based on purchase orders issued by reputable manufacturers. POF lenders include traditional commercial banks and specialized POF lenders Martin (2010); Tice (2010). Unlike asset-based loans or factoring, which are backed by tangible assets, the repayment of a POF loan depends on the supplier's successful delivery of the associated purchase order. Because a POF loan is only granted based on purchase orders issued by creditworthy buyers, the major risk associated with POF is not the buyer's credit risk but the supplier's *performance risk*, that is, the supplier may fail to deliver the order according to the buyer's specifications on quality, timeliness, or compliance Gustin (2014).

Under the second scheme, which we call *Buyer Direct Financing* (BDF), manufacturers act as both the buyers and the lenders and directly finance their suppliers for production.

BDF has been adopted by manufacturers and supply chain intermediaries in both developed and developing markets. Since 2009, Rolls-Royce has lent over £500 million to small suppliers unable to obtain adequate financing through other channels. Similarly, GlaxoSmithKlein (GSK) has lent billions of pounds to its suppliers Watkins (2012). Li & Fung, the global supply chain intermediary based in Hong Kong, has financed some of its long-term suppliers so that they can initiate production for Li & Fung's order Fung et al. (2007). BDF can also take the form of procuring raw materials for suppliers. For example, Hanbo Enterprise Holdings, a Hong Kong-based supply chain intermediary specializing in the apparel sector, procures fabrics for its suppliers and treats procurement costs as interest-bearing loans Cheng (2015).

As both POF and BDF are taking shape, industry experts are debating whether financial intermediaries (i.e. banks and specialized lenders) or supply chain partners (i.e. manufacturers or supply chain intermediaries) are in a better position to finance suppliers. On the one hand, many critics argue that manufacturers should leave financing to professionals with domain expertise. On the other, supply chain experts argue that with their unique position in the supply chain, manufacturers are able to provide financing more efficiently. Indeed, as both POF and BDF are closely related to suppliers' performance risk, the efficiency of these two financing schemes hinges upon on how to manage such risk. With close operational relationships with suppliers, manufacturers have better control over and knowledge of suppliers Fung et al. (2007). For instance, manufacturers can design supply contracts to incentivize suppliers to improve delivery performance by exerting efforts in areas such as quality control and process improvement Aydin et al. (2011). By optimizing the supply contract and financing terms together with suppliers, manufacturers may be able to exert better control over suppliers. Furthermore, manufacturers often have better information than banks about suppliers' intrinsic operational efficiency due to previous interactions, extensive auditing, or domain knowledge of particular purchase orders. Therefore, the loss in efficiency due to information asymmetry may be lower under BDF than POF. By considering these issues, we examine two research questions in this paper:

1. By combining the role of buyer and lender, can BDF better incentivize suppliers to improve performance?

2. Does manufacturers' information advantage about suppliers (compared to banks) make BDF a superior financing scheme?

To answer the first question, we analyze a Stackelberg game that involves three parties: a manufacturer, a supplier with limited assets who can exert unobservable and costly effort to improve delivery reliability, and a bank operating in a competitive lending market (note that the bank only plays a role in POF). To enable the supplier to start production, the manufacturer either finances the supplier directly under BDF or offers a sourcing contract that allows the supplier to secure a loan through POF. Our equilibrium analysis has the following implications. First, when the supplier's asset value is below a certain threshold, the supplier cannot obtain financing through either schemes. Second, when the supplier's asset value exceeds this threshold, both POF and BDF would yield the same performance in terms of the supplier's delivery reliability and the manufacturer's payoff, even though BDF gives the manufacturer more flexibility in selecting financing terms. Such flexibility not only explains why manufacturers offer diverse interest rate under BDF but also suggests that BDF is particularly valuable in markets where interest rates are heavily regulated, as is the case in many developing countries including China and India. By contrast, POF is more appealing if the bank enjoys a lower cost of capital or of issuing/administrating loans.

To answer the second question, we extend the above model by considering the case where the market is comprised of two types of suppliers: "efficient," with low (effort) cost factors, and "inefficient," with high cost factors. We examine a situation where the manufacturer knows a supplier's actual type but the bank only knows its distribution. Because the manufacturer knows the supplier's actual type and the bank is not involved under BDF, the performance of BDF remains the same as before. However, POF may become less efficient in this case due to the bank's information disadvantage. To capture the interactions between all three parties, we use a signaling game in which the manufacturer uses her contract price to signal her private information about the supplier's actual type to the bank. Our equilibrium analysis reveals that from the manufacturer's perspective, BDF and POF yield the same payoff when the supplier's asset value is sufficiently high, in spite of the bank's information disadvantage. However, BDF is more valuable when the supplier is efficient but has sufficiently low asset value. Finally, we find that BDF is relatively more appealing when the market has a higher percentage of inefficient suppliers or when the manufacturer's alternative sourcing option is more expensive. This finding highlights that information advantage plays an important role in the manufacturer's advantage of financing suppliers, rationalizing why BDF is mostly offered by manufacturers or intermediaries to long-term suppliers or suppliers with specialized skills.

The rest of this paper is structured as follows. We summarize the related literature in Section 3.2. Sections 3.3 and 3.4 study the optimal sourcing contract with POF and BDF, respectively, when the manufacturer and bank have symmetric information. Section 3.5 extends the model to examine the implications of information asymmetry when the supplier's cost factor is known to the manufacturer but not to the bank. We conclude the paper in Section 3.6. All proofs are provided in the Appendix.

3.2 Related Literature

As an initial attempt at understanding the relative efficiency of POF and BDF under the supplier's endogenous effort and manufacturer's private information, this chapter is related to three research streams: supply risk management, supply chain finance, and signaling games.

Supply risk management is an important research topic in operations. See Sodhi and

Tang (2012) and Kouvelis et al. (2011), in particular Tomlin and Wang (2011), for a comprehensive overview of this topic. Similar to recent papers such as Aydin et al. (2011), Li (2013), Tang et al. (2014), and Hwang et al. (2014), this chapter focuses on designing supply contracts to incentivize suppliers to improve operational performance. Another related literature stream focuses on managing financially distressed suppliers. Swinney and Netessine (2009) show that long-term contracts can be used to reduce suppliers' default risk. Babich (2010) characterizes manufacturers' joint subsidy and capacity reservation policies when facing financially distressed suppliers. Dong and Tomlin (2012) and Dong et al. (2015) examine how insurance can interact with operational strategies in mitigating supply risk when the chain is subject to financing costs. This chapter complements the supply risk literature by focusing on the interaction between suppliers' financial constraints and endogenous performance and highlighting that selecting financing schemes properly plays a crucial role in manufacturers' sourcing decisions and profitability.

Next, this chapter is related to the supply chain finance literature. By examining financing schemes offered by buyers to suppliers, this chapter is related to Chen and Gupta (2014) and Tunca and Zhu (2014), who show that in the presence of demand risk, reverse factoring can increase stocking levels and hence yield higher supply chain performance. This chapter complements this literature by serving as the first attempt at examining the implications of financing schemes for supply risk. The majority of supply chain finance papers focus on trade credit, i.e. the credit extended by suppliers to buyers. Babich and Tang (2012) and Rui and Lai (2015) characterize the optimal trade credit policy to deter suppliers' moral hazard. Kouvelis and Zhao (2012) and Yang and Birge (2009) show that trade credit can improve supply chain efficiency by acting as a risk-sharing mechanism. Petersen and Rajan (1997) and Biais and Gollier (1997) argue that one reason suppliers offer trade credit to their buyers is because of their information advantage. While the financing schemes examined in this paper share some similarities with trade credit, our setting is based on the buyer (or the bank) who lends to the supplier. Related to this literature, our results suggest that there are two fundamental differences, justifying why BDF is not as prevalent as trade credit. First, when the manufacturer and bank have symmetric information, as the contract price is already contingent on whether the supplier can fulfill the order successfully, adding interest rates as an additional lever does not further mitigate the supplier's performance risk. This distinguishes our models from the trade credit model, as examined by Kouvelis and Zhao (2012) and Yang and Birge (2009). Second, when the manufacturer has superior information about the supplier compared to the bank, she may use the contract price to credibly signal her private information to the bank with minimal costs, making POF a viable financing scheme. Differently, in Biais and Gollier (1997), when selling to the buyer, contract price alone cannot signal the buyer's type to the buyer's external investor, hence leaving the signaling role to trade credit. That said, our analysis does point out that compared to POF, BDF offers more flexibility for the manufacturer to select financing terms. BDF is also more appealing when the manufacturer has superior information about the supplier compared to the bank and the supplier's asset value is low.

Finally, our analysis of POF in the presence of information asymmetry between the manufacturer and bank is casted as a *signaling game* Riley (2001); Spence (2002). In the OM literature, Cachon and Lariviere (2001) was the first paper to study how firms can signal their private information on quantities to their supply chain partners. Recent papers in the operations-finance interface literature, including Lai et al. (2011), Schmidt et al. (2015), and Lai and Xiao (2014), study how firms can signal demand information to external investors through inventory decisions. In the same spirit, our model examines how the manufacturer can signal her private information about the supplier's type to the bank. However, we differ from the aforementioned papers in two ways. First, our model examines the issue of signaling in the context of *debt financing* rather than *equity financing*. Specifically, when the supplier's asset level is low, the signal the manufacturer can send is bounded by the bank's lending constraint so that the pooling equilibrium may be the stable dominant equilibrium. This result complements the results obtained by the aforementioned papers, which find that the pooling equilibrium is more appealing in various other settings. Second, different from the extant literature, our signaling game involves three parties, introducing some interesting dynamics. Specifically, when the supplier's asset value is high, we find that the separating equilibrium is *costless* because the supplier's own participation constraint can be used by the manufacturer to credibly signal the bank about the supplier's type.

3.3 Sourcing with POF

We start our analysis by focusing on how sourcing contracts and financing schemes can jointly control suppliers' moral hazard. We examine this issue under the POF scheme in this section and then examine the BDF scheme in Section 3.4. Section 3.5 extends the model to examine the relative attractiveness of both financing schemes in the presence of both moral hazard and information asymmetry.

3.3.1 The Model

Consider a supply chain comprising a manufacturer (she), a supplier (he), and a bank (it). All parties are assumed to be risk neutral. In the following, we describe the operational aspect of the model followed by the financial aspect.

Supply Chain Operations.

Consider a supply chain comprising one manufacturer and one supplier. Focusing on supply risk, the demand faced by the manufacturer is assumed to be constant and is normalized to 1 without loss of generality. To satisfy this demand, the manufacturer needs to decide whether to source from the supplier, who is inherently unreliable and can only deliver the order with a certain probability. To fulfill the order, the supplier incurs a monetary production cost $c > 0$ to cover raw materials, wages, equipment, etc. In addition, the supplier can exert unobservable and costly efforts (e.g. improve production processes) to improve his delivery probability.

Without loss of generality, we scale the base delivery probability to 0; however, the supplier can exert costly effort to increase the delivery probability from 0 to e, where $e \in (0, 1)$.[1] We assume that the cost associated with this effort is convex and increasing in e. Following the literature Li (2013), we assume that the supplier's disutility of exerting effort (the cost of effort) is ke^2, where k is the supplier's (effort) cost factor. We capture the supplier's operational efficiency as follows: An efficient supplier has a lower k so that he can achieve a higher delivery probability at a lower effort cost. In our base model, k is assumed to be common knowledge to all parties.[2]

We assume that the manufacturer acts as the Stackelberg leader, who sets the contract price, and the supplier acts as the follower, who decides whether to accept the supply contract. Without loss of generality, we focus on the following contingent contract: The manufacturer pays the supplier the contract price p upon successful delivery and zero otherwise.[3] In the event that the supplier fails to deliver, the manufacturer will source the product from an alternative, emergency channel at cost v. (If the manufacturer chooses not source from the unreliable supplier, she can always source from this alternative channel at cost v.) Therefore, the manufacturer's *payoff* Π_M can be measured in terms of the *expected cost savings* generated from sourcing through the unreliable supplier, where $\Pi_M = v - [ep + (1-e)v] = e(v-p)$.

1. In a different context, this setup is similar to Porteus (1985), who examines the implications of reducing setup costs in the EOQ model by investing in process improvement.

2. Section 3.5 extends the model to the case where the exact value of k is known only to the manufacturer and supplier, while the bank only knows the distribution.

3. In our model, due to the supplier's financial constraint, which is detailed later, this class of contract is indeed the only class that needs to be considered. It is clear that offering the supplier a positive payment upon failed delivery aggravates the supplier's moral hazard. On the other hand, penalizing the supplier (a negative payment) upon failed delivery does not better mitigate his moral hazard due to the supplier's financial constraint. See Proposition D.0.1 in the Appendix for the technical details.

The Supplier's Financial Constraints and POF.

As a salient feature of our model, the supplier is assumed to be financially constrained. Specifically, the supplier has only liquid assets to the value of a, which is less than his production cost c (i.e. $a < c$), and no cash to hand. We refer to $(c - a)$ as the supplier's *net financing need*. With the manufacturer's purchase order as the only future income, the supplier has to borrow c externally to initiate production and fulfill the manufacturer's order.[4]

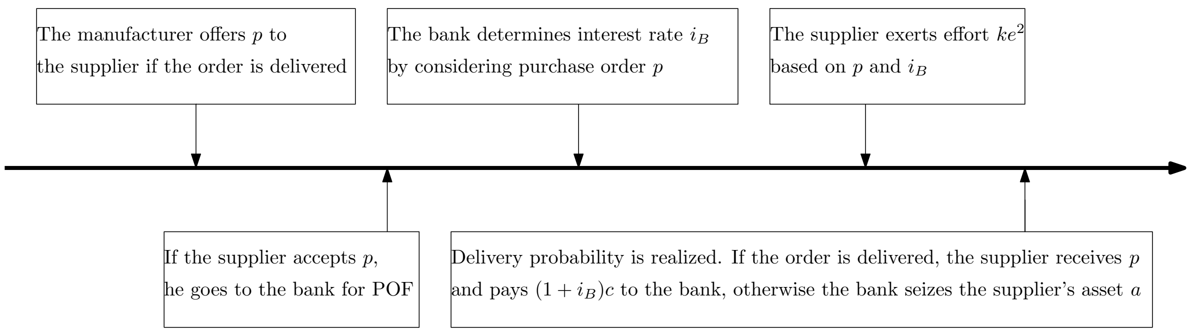
Under POF, assuming that the contingent contract price p is acceptable to him, the supplier takes the purchase order to the bank and applies for a POF loan in the amount of c. By considering the purchase order with contingent payment p, the bank decides whether to lend c to the supplier and, if so, what interest rate i_B to charge. Under this POF loan contract, if the supplier's delivery is successful, then the supplier receives payment p from the manufacturer, pays the principal and interest $(1 + i_B)c$ to the bank, and keeps the rest. If delivery is not successful, the supplier receives no payment, the POF loan is in default, the bank seizes the supplier's liquid assets a, and the supplier is left with nothing. To focus on the supplier's performance risk, we assume that the manufacturer has no credit risk and will pay the supplier as long as the order is delivered successfully. The bank is assumed to operate in a competitive lending market, and hence it sets the interest rate so that the lending amount c equals its expected payoff discounted at the bank's cost of capital, which is normalized to zero. Under the POF scheme, the supplier's objective is to maximize his expected payoff $\Pi_S = e[p - (1 + i_B)c] - (1 - e)a - ke^2$, which accounts for the expected gain upon successful delivery (after paying off the loan plus interest) $e[p - (1 + i_B)c]$, the expected loss of assets for the lender in the event of delivery failure $(1 - e)a$, and the cost of effort ke^2. Normalizing his outside option to 0, the supplier accepts a contract only when

4. Alternatively, we can assume that the supplier has cash a and need only borrow $c - a$. All results in the model remain qualitatively unchanged.

$\Pi_S \geq 0$.

Combining the operational and financial aspects of the model, the sequence of events is summarized in Figure 3.1.

Figure 3.1: Sequence of Events under POF



The First-best Benchmark.

Before we analyze the Stackelberg game as depicted in Figure 1, let us first establish the first-best benchmark by analyzing a centralized controlled supply chain. Without the need to consider payment to the supplier within a centralized controlled system, the expected savings associated with sourcing from an internal supplier are equal to $\Pi_C = v - [c + ke^2 + (1-e)v] = ev - c - ke^2$.

Lemma 3.1. *In a centralized supply chain, the manufacturer sources from the supplier if and only if* $\frac{v^2}{4k} \geq c$*. The resulting delivery probability is* $e^* = \frac{v}{2k}$*, and the corresponding chain payoff is* $\Pi_C^* = \frac{v^2}{4k} - c$*.*

It follows from Lemma 3.1 that to capture some delivery risk so that $e^* = \frac{v}{2k} < 1$ and to ensure that the manufacturer has an incentive to source from the unreliable supplier so that $\Pi_C^* = \frac{v^2}{4k} - c > 0$, we shall assume $k \in \left(\frac{v}{2}, \frac{v^2}{4c}\right)$ throughout this chapter.

3.3.2 The Supplier's Effort under POF

We now solve the Stackelberg game as depicted in Figure 3.1 by backward induction. First, given any contingent price p and interest rate i_B, the supplier's problem can be formulated as: $\max_e \ \Pi_S = \max_e = e[p - (1+i_B)c] - (1-e)a - ke^2$. By considering the first order condition, the supplier's best response is given as:

$$e(p, i_B) = \frac{p - (1+i_B)c + a}{2k}. \tag{3.1}$$

From (3.1), it is clear that the supplier's delivery probability e is increasing in the contingent price p and his asset value a but is decreasing in the interest rate i_B, production cost c, and cost factor k. By substituting (3.1) into the supplier's payoff Π_S, it is easy to check that $\Pi_S = \frac{[p-(1+i_B)c+a]^2}{4k} - a$, suggesting that the supplier's participation constraint associated with (p, i_B), which has $\Pi_S \geq 0$, can be written as:

$$p \geq (1+i_B)c + 2\sqrt{ka} - a. \tag{3.2}$$

3.3.3 The Equilibrium POF Interest Rate

Next, observing the contract price p, the bank can anticipate the supplier's effort $e(p, i_B)$ as given in (3.1). Operating in a competitive lending market, the bank sets its interest rate i_B to break even in expectation, i.e. $e(1+i_B)c + (1-e)a = c$.[5] Substituting e given in (3.1), the equilibrium interest rate for any given p satisfies:

$$i_B(p) = \frac{p - \sqrt{p^2 - 8k(c-a)}}{2c} + \frac{a}{c} - 1. \tag{3.3}$$

5. In the presence of multiple solutions to the equation, competition should push the bank to offer the lowest interest rate.

Observe from (3.3) that for the bank to offer POF, the contingent price p the manufacturer offers has to be sufficiently high relative to the supplier's net financing need $(c-a)$ and his cost factor k, or more specifically, $p^2 \geq 8k(c-a)$.

3.3.4 The Optimal Sourcing Contracts under POF

By using the equilibrium interest rate given in (3.3), the corresponding supplier's best response given in (3.1) can be rewritten as:

$$e(p) = \frac{p + \sqrt{p^2 - 8k(c-a)}}{4k} \tag{3.4}$$

and the supplier's participation constraint (3.2) can be rewritten as:

$$p + \sqrt{p^2 - 8k(c-a)} \geq 4\sqrt{ka}. \tag{3.5}$$

Observe from (3.5) that it characterizes the condition for the contingent price p to be *jointly acceptable* to both the supplier and the bank. Specifically, (3.5) can be further simplified into two scenarios, depending on the relationship between a and $\frac{c}{3}$. First, when $a < \frac{c}{3}$, the supplier has little to lose and is therefore willing to accept any p as long as the bank is willing to lend. In this case, (3.5) can be simplified as $p \geq p^{BL} := \sqrt{8k(c-a)}$, that is, the price p is jointly acceptable if the *bank's lending condition (BL)* is satisfied. Next, when $a \geq \frac{c}{3}$, the bank can recover more by liquidating the supplier's assets when he fails to deliver and hence is willing to lend as long as p is acceptable to the supplier. In this case, (3.5) can be simplified as $p \geq p^{SA} := 2\sqrt{ka} + \frac{k(c-a)}{\sqrt{ka}}$, i.e. p is jointly acceptable if the *supplier's acceptance condition (SA)* is satisfied.

Anticipating the supplier's best response e given in (3.4), the manufacturer's payoff $\Pi_M =$

$e(v-p)$ can be expressed as:

$$\Pi_M = \frac{p+\sqrt{p^2-8k(c-a)}}{4k}(v-p). \tag{3.6}$$

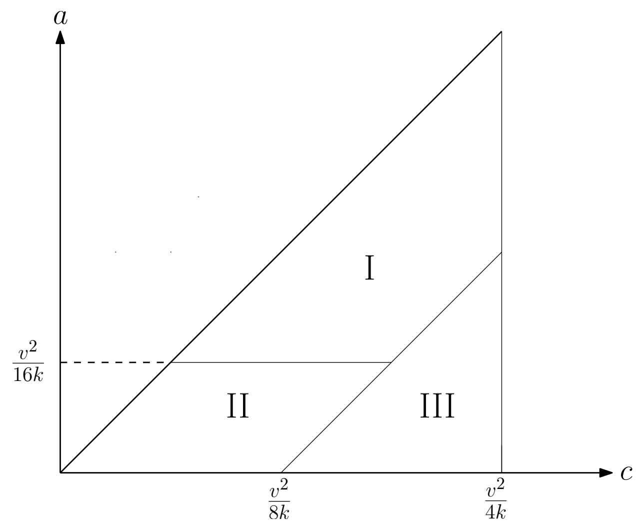
In this case, the manufacturer's problem can be formulated as: $\max_p \ \Pi_M$, subject to (3.5). By considering the first order condition, we can determine the optimal POF contract. Through substitution, we can determine the equilibrium outcomes in Proposition 3.3.1.

Proposition 3.3.1. *Under POF, the equilibrium outcomes are as follows:*

1. *When* $a > \max\{c-\frac{v^2}{8k},\ \frac{v^2}{16k}\}$*, the manufacturer offers* $p^* = p^{SA}$*, the bank lends to the supplier at interest rate* $i_B^* = \left(\sqrt{\frac{k}{a}}-1\right)\left(\frac{c-a}{c}\right)$*, and the equilibrium delivery probability* $e^* = \sqrt{\frac{a}{k}}$. $\Pi_M^* = v\sqrt{\frac{a}{k}} - c - a$ *and* $\Pi_S^* = 0$.
2. *When* $a \in \left[c-\frac{v^2}{8k}, \frac{v^2}{16k}\right]$*, the manufacturer offers* $p^* = \frac{v}{2}+\frac{4k(c-a)}{v}$*, the bank lends to the supplier at interest rate* $i_B^* = \left(\frac{4k}{v}-1\right)\left(\frac{c-a}{c}\right)$*, and the equilibrium delivery probability* $e^* = \frac{v}{4k}$. $\Pi_M^* = \frac{v^2}{8k}-(c-a)$ *and* $\Pi_S^* = \frac{v^2}{16k} - a$.
3. *When* $a < c - \frac{v^2}{8k}$*, the manufacturer does not source from the supplier.* $\Pi_M^* = \Pi_S^* = 0$.

By using the assumption that $a > c$ and $\Pi_C^* = \frac{v^2}{4k} - c > 0$ (from Lemma 1), we can illustrate the results as stated in Proposition 3.3.1 in Figure 3.2. First, when the supplier's asset value $a > \max\{c-\frac{v^2}{8k},\ \frac{v^2}{16k}\}$ (Region I), the supplier has a stronger incentive to exert more effort to increase his delivery probability e^* so as to protect his assets. Recognizing this, it is optimal for the manufacturer to offer the lowest price acceptable to the supplier so that $p^* = p^{SA}$. Within this region, as the supplier's asset value a decreases, the first statement suggests that the supplier's delivery probability e^* declines. As supply risk increases, the bank's interest rate i_B increases. Consequently, the supplier's lowest acceptable price p^{SA} increases and the manufacturer ends up paying a higher contingent price $p^* = p^{SA}$.

Figure 3.2: Different Regions under the Optimal POF Contract



Next, when the supplier's asset level a drops below $\frac{v^2}{16k}$ but the net financing need $(c-a)$ is not too large (Region II), the supplier has little to lose and a greater incentive to shirk his efforts to improve his delivery probability. To mitigate supply risk, the manufacturer has to offer a contingent price p^* that is above p^{SA} so as to entice the supplier to exert some effort to increase his delivery probability e^*. Within Region II, as the supplier's asset value a decreases, the manufacturer increases the equilibrium price p^* to completely offset the increasing interest rate i_B^*, resulting in a constant net margin $(p^* - (1 + i_B^*)c)$ for the supplier and, therefore, a constant delivery probability $e^* = \frac{v}{4k}$, which is strictly lower than the corresponding delivery probability $e^* = \sqrt{\frac{a}{k}}$ in Region I.

Finally, when the supplier's asset level $a < c - \frac{v^2}{8k}$ (Region III), it is easy to check that $p^{BL} = \sqrt{8k(c-a)} > v$, which implies that in order to satisfy the bank's lending condition, the manufacturer has to offer a contract price that is greater than v. In this case, it is certainly not economical for the manufacturer to source from the unreliable supplier.

Moreover, it is easy to check from Proposition 3.3.1 that the equilibrium delivery probability e^* and the supply chain payoff $\Pi_M^* + \Pi_S^*$ are lower than the corresponding quantities under the first-best benchmark as presented in Lemma 1. It is well known that when the supplier's asset level is sufficiently high, the manufacturer can design a contract to achieve the first-best benchmark and extract all profit Laffont and Martimort (2009). However, when the supplier is financially constrained, our results stated in Proposition 3.3.1 imply that the supplier's financial constraint reduces the delivery probability and supply chain profitability.

Besides the supplier's asset value a, it is easy to check that the supplier's cost factor k affects the optimal contract and equilibrium outcomes as follows.

Corollary 3.3.1. *In equilibrium, the manufacturer's contract price p^* and the bank's interest rate i_B^* increase in the supplier's cost factor k. However, the equilibrium delivery probability e^*, manufacturer's payoff Π_M^*, and supplier's payoff Π_S^* decrease in k.*

When the supplier becomes less efficient (i.e. has a higher cost factor k), Corollary 1 reveals that the manufacturer needs to offer a higher contract price p^* to compensate for the higher interest rate i_B^* charged by the bank. Nevertheless, the equilibrium delivery probability e^* is decreasing in k. This result suggests that when the manufacturer sources from an inefficient supplier, she faces a higher supply risk (due to lower e^*) and pays a higher contract price.

3.4 Joint Sourcing and Financing under BDF

Relative to the first-best benchmark presented in Lemma 1, Proposition 3.3.1 reveals that the supplier's financial constraint lowers supply chain payoff $\Pi_M^* + \Pi_S^*$ and delivery probability e^* under POF. Is this supply chain inefficiency caused by the fact that under POF, the sourcing contract and interest rate are determined separately by the manufacturer and the bank, respectively? We know that in the trade credit literature, supply chain efficiency can be improved when the manufacturer sets the wholesale price and the trade credit (Kouvelis and Zhao (2012), Yang and Birge (2009)). Does this result hold in our setting? Specifically, will BDF improve supply chain efficiency when the sourcing contract and interest rate are both determined by the manufacturer? We examine these questions in this section.

Under BDF, the manufacturer determines both the contingent price p and interest rate i_M (for lending c to the supplier) and the bank does not play a role. Upon successful delivery, the manufacturer deducts the principal and interest $(1+i_M)c$ from p and pays the rest to the supplier. When the supplier fails to deliver, the manufacturer does not pay the supplier and seizes the supplier's assets a to partially recover the (defaulted) loan c. To compare BDF and POF directly, we assume that the manufacturer's cost of capital is also zero, the same as the bank's.

We now analyze the corresponding Stackelberg game via backward induction. First, for any given (p, i_M), the supplier's best response is the same as described in Section 3.3.2 and hence the supplier's best response $e(p, i_M)$ and acceptance condition are given in (3.1) and (3.2), respectively, with i_B being replaced by i_M.

Anticipating the supplier's response, the manufacturer chooses p and i_M jointly to maximize her payoff, which includes not only the expected operational saving $e(v-p)$ but also her financing earnings from the BDF loan, $e(1+i_M)c+(1-e)a-c$. Combining the two components, the manufacturer's payoff under BDF can be expressed as: $\Pi_M = e(v-p) + [e(1+i_M)c + (1-e)a - c]$. In this case, the manufacturer's problem can be formulated as: $\max_{p,i_M} \Pi_M$, subject to (3.1) and (3.2), with i_B being replaced by i_M. By considering the first order condition, we establish Proposition 3.4.1.

Proposition 3.4.1. *Under BDF, the joint optimal contract (p^*, i_M^*) is given as follows.*

1. *When $a > \max\{c - \frac{v^2}{8k}, \frac{v^2}{16k}\}$, (p^*, i_M^*) is optimal if and only if $p^* - (1+i_M^*)c = 2\sqrt{ka} - a$.*

2. *When $a \in \left[c - \frac{v^2}{8k}, \frac{v^2}{16k}\right]$, (p^*, i_M^*) is optimal if and only if $p^* - (1+i_M^*)c = \frac{v}{2} - a$.*

3. *When $a < c - \frac{v^2}{8k}$, the manufacturer does not source from the supplier.*

In all three scenarios, under the optimal BDF contract (p^*, i_M^*), the equilibrium delivery probability e^* and the manufacturer's and supplier's payoffs (i.e. Π_M^* and Π_S^*) are identical *to those presented in Proposition 3.3.1 under POF.*

Proposition 3.4.1 asserts that compared to POF, BDF does not improve supply chain efficiency even though the contingent payment and interest rate are both determined by the manufacturer. This result can be explained as follows. Recall from above that for any given (p, i), the supplier's best response (i.e. delivery probability e) is given in (3.1) and it does not matter whether the lender is the bank (under POF) or the manufacturer (under BDF). As such, the manufacturer does not gain much by serving as the lender under BDF.

While BDF and POF yield the same supply chain efficiency, Proposition 3.4.1 reveals that BDF does offer the manufacturer more flexibility in setting p^* and i_M^*. That is, p^* and i_M^* can induce optimal performance as long as $p^* - (1 + i_M^*)c$ stays constant. This flexibility provides a plausible reason why some manufacturers offer low interest rates in some BDF programs. For example, GSK lends money to its suppliers at the same interest rate that GSK pays the bank (Watkins (2012)), while Hanbo finances its suppliers at an interest rate that is effectively lower than the bank rate (Cheng (2015)). Such flexibility can also be valuable for the manufacturer as a means of circumventing regulations. For instance, when the supplier's asset value is low, under POF, the interest rate has to be set very high to compensate for the associated risk. However, in certain markets, such as China and India, regulations may cap interest rates below certain levels, rendering POF infeasible. In this case, the manufacturer can simply lower the contract price and interest rate simultaneously under BDF, allowing the supplier to obtain financing. Additionally, our model of POF assumes a perfect competitive lending market. However, in less competitive lending markets, POF can also create an additional double marginalization, making BDF more attractive. Therefore, we should expect that manufacturers may finance suppliers directly in emerging economies where the financial market is less open.

Finally, to focus on the performance of POF and BDF on mitigating the supplier's performance risk, our model assumes that the manufacturer and the bank have identical costs of capital and ignores the fixed cost of loan assessment and administration as well as asset liquidation in the event of failed delivery. Taking these factors into consideration, one might argue that the bank will have lower costs due to its economies of scale and domain expertise in the above areas. These factors could potentially make POF more attractive than BDF. This is consistent with anecdotal evidence that only large manufacturers or intermediaries with a large supply base lend directly to their suppliers.

3.5 The Implications of the Manufacturer's Information Advantage

Even when the manufacturer determines both the contingent payment and interest rate under BDF, we have learned from Proposition 3.3.1 and Proposition 3.4.1 that BDF does not outperform POF in terms of higher delivery probably e^* and higher manufacturer's payoff Π_M. Is this finding caused by the fact that both the manufacturer and the bank have perfect information about the supplier's cost factor k? Does BDF outperform POF when the manufacturer has more accurate information about the supplier than the bank? In practice, the manufacturer may have more intimate knowledge about the supplier than the bank because the manufacturer has conducted business with the supplier before or because the manufacturer has better domain knowledge for evaluating the supplier's operational efficiency. For example, Li & Fung audits suppliers extensively before conducting business with them. Through such audits, Li & Fung acquires in-depth knowledge about the supplier's operations excellence (facility, equipment, lean, quality improvement), human capital strengths (employee development and training programs), and compliance with environmental and safety regulations. These factors are often not assessed thoroughly by banks. Another source of information advantage originates from the manufacturer's better understanding of the operational specifics of a particular purchase order. Clearly, such information advantage is present even when the bank has also conducted business with the supplier. Given the manufacturer's information advantage (over the bank), is BDF always the preferred financing channel?

To answer these questions, we extend the base model to the case where the manufacturer has an information advantage over the bank about the supplier's cost factor k. Specifically, consider the case where there are two types of suppliers in the market: *efficient* suppliers ($\tau = H$), with cost factor $k = k_H$, and *inefficient* suppliers ($\tau = L$), with cost factor k_L, where $k_H < k_L$. To capture the manufacturer's information advantage, we assume that the manufacturer and the supplier know the exact type that a supplier is but the bank only knows the distribution, so that the supplier is type H with probability λ (and is type L with probability $(1 - \lambda)$.

Because there is no information asymmetry about the supplier's exact type τ between the manufacturer and the supplier, the optimal contract and equilibrium outcome under BDF remain the same as stated in Proposition 3.4.1, with k being replaced by k_τ. Therefore, it suffices to focus our analysis on POF in the presence of information asymmetry between the manufacturer and the bank.

3.5.1 *The Signaling Game under POF*

Following the sequence of events under POF as depicted in Figure 1, we model the interaction between the manufacturer, the bank, and the supplier as a signaling game. As the party with private information, the manufacturer (the "sender" of the signal) first offers a supply contract with price p (the signal) to the supplier, who in turn takes the contract to obtain financing from the bank (the "receiver" of the signal). Upon receiving the signal, the bank forms a posterior belief about the supplier's type and offers financing terms accordingly. In essence, the sequence of events is the same as depicted in Figure 3.1, except that after seeing the purchase order, the bank updates its belief about the supplier's type using Bayes' rule, as detailed later.

As in the signaling games literature, the equilibrium concept adopted in the signaling game is the Perfect Bayesian Equilibrium (PBE), which includes a sequentially rational strategy profile and the bank's posterior belief. The strategy profile consists of the contingent price (p_τ^*) offered by the manufacturer to a type-τ supplier, the interest rate ($i_{B,\tau'}^*$) offered by the bank under its belief of the supplier's type τ', and the supplier's delivery probability e_τ^* selected by a type-τ supplier in response to p_τ^* and $i_{B,\tau'}^*$. Without loss of generality, we focus on pure strategy equilibria. As such, two possible types of PBE arise from the above signaling game: *separating equilibria* and *pooling equilibria*. In a separating equilibrium, the manufacturer offers different prices (p_H^* and p_L^*) to different types of suppliers, which can credibly signal the suppliers' actual types to the bank, and the bank can then update the suppliers' types with certainty, i.e. $\mu = 0$ or 1, where μ is the bank's posterior probability that the supplier is efficient ($\tau = H$). In a pooling equilibrium, the manufacturer offers the same price p_W^* regardless of the supplier's actual type. Hence, the bank finds the signal uninformative, so that its posterior belief is the same as its prior, i.e. $\mu = \lambda$, and offers interest rate $i_{B,W}^*$ accordingly.[6]

In the remainder of this section, we characterize the separating and pooling equilibria in Sections 3.5.2 and 3.5.3, respectively. Equilibrium refinement is discussed in Section 3.5.4. Section 3.5.5 concludes by discussing the implications of information asymmetry for the efficiency of POF relative to BDF. To avoid trivial cases, we confine our analysis to the parameter space $\Omega := \left\{(c,a) \mid c - \frac{v^2}{8k_H} \leq a \leq c \leq \frac{v^2}{4k_H}\right\}$ (i.e. Regions I and II in Figure 3.2 with $k = k_H$), which ensures that the manufacturer will at least source from the efficient (type-H) supplier under symmetric information according to Proposition 3.3.1.

6. The subscript W represents "weighted." With slight abuse of notation, in the rest of this section we use $\tau = W$ to represent the corresponding quantities when the bank's posterior belief is the same as its prior, i.e. in the pooling equilibrium.

3.5.2 Separating Equilibria under POF

We begin our analysis of the separating equilibria by examining the supplier's best response e_τ^* and the bank's interest rate $i_{B,\tau'}^*$ under contract price p_τ and the bank's belief about the supplier's type (τ'), where $\tau,\ \tau' \in \{H,\ L\}$. As there is no information asymmetry between the manufacturer and the supplier, the supplier's response to any given price p and interest rate i_B is exactly the same as in Section 3.3.2. By considering (3.1) and (3.2), the supplier's best response can be written succinctly as:

$$e_\tau^*(p, i_B) = \frac{p - (1 + i_B)c + a}{2k_\tau} \cdot \mathbb{1}_{\{p \geq (1+i_B)c + 2\sqrt{k_\tau a} - a\}}, \tag{3.7}$$

where the supplier's acceptance constraint (3.2) is embedded in the indicator function $\mathbb{1}_x$. Note that as $k_L > k_H$, the inefficient supplier's acceptance constraint is more strenuous than that of an efficient supplier. Therefore, for any given interest rate i_B, there exists a certain price p that is acceptable to the efficient supplier but not to the inefficient one.

Anticipating the supplier's best response e_τ^*, the bank sets the interest rate i_B so that its expected payoff based on its belief of the supplier's type τ' is equal to the lending amount c. By considering (3.3), with k being replaced by $k_{\tau'}$, the bank's interest rate can be written succinctly as:

$$i_{B,\tau'}^* = \begin{cases} \frac{p - \sqrt{p^2 - 8k_{\tau'}(c-a)}}{2c} + \frac{a}{c} - 1 & \text{if } \ p \geq \sqrt{8k_{\tau'}(c-a)}. \\ \infty & \text{otherwise.} \end{cases} \tag{3.8}$$

Notice that $i_{B,H}^* \leq i_{B,L}^*$, which implies that the bank will offer a lower interest rate if it believes that the supplier is efficient $(\tau' = H)$.

The Manufacturer's Payoff under POF.

In order to determine the manufacturer's contract price $p_\mathcal{T}$ in separating equilibria, let us first define the manufacturer's payoff function when the supplier's actual type is $\tau \in \{H, L\}$, the bank's belief about the supplier type is $\tau' \in \{H, L\}$, and the manufacturer offers price p. Analogous to the perfect information case presented in Section 3.1.1, the manufacturer's payoff equals $\Pi_M(\tau, p, \tau') = e^*_\tau(p, i^*_{B,\tau'})(v-p)$. By using (3.7) and (3.8), we can rewrite the manufacturer's payoff succinctly as:

$$\Pi_M(\tau, p, \tau') = \frac{p + \sqrt{p^2 - 8k_{\tau'}(c-a)}}{4k_\tau}(v-p) \cdot \mathbb{1}_{\left\{p+\sqrt{p^2-8k_{\tau'}(c-a)} \geq 4\sqrt{k_\tau a}\right\}}, \tag{3.9}$$

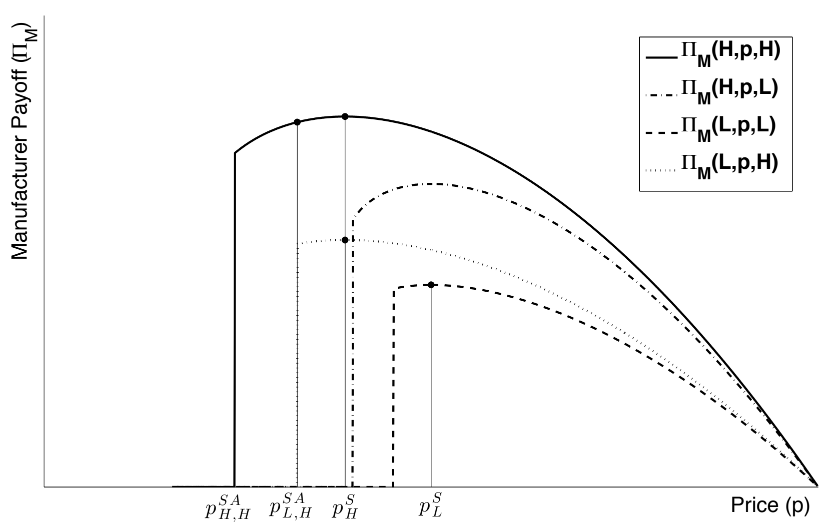
Figure 3.3 illustrates the manufacturer's payoff $\Pi_M(\tau, p, \tau')$. Also shown in Figure 3.3 are the optimal contingent prices under symmetric and perfect information for the different types of suppliers: $p^S_\tau = \arg\max = \Pi_M(\tau, p, \tau)$ for $\tau = H, L$. Notice that these are the same optimal contract prices as stated in Proposition 3.3.1, with k being replaced by k_τ for $\tau = H, L$.

Akin to (3.5), as in the symmetric and perfect information case, the indicator function in (3.9) captures the condition that the contract price p is *jointly acceptable* to both the supplier and the bank if and only if it is higher than a certain "minimal acceptable price." Instead of the relative magnitude between a and $c/3$, as in the symmetric information case discussed in Section 3.4, the minimal acceptable price in the asymmetric information case depends on the relative magnitude between a and $\frac{c}{\left(1+\frac{2k_\tau}{k_{\tau'}}\right)}$. First, when $a < \frac{c}{\left(1+\frac{2k_\tau}{k_{\tau'}}\right)}$, p is jointly acceptable as long as it satisfies the bank lending condition (BL) under the bank's believed type τ', i.e. $p \geq p^{BL}_{\tau'} := \sqrt{8k_{\tau'}(c-a)}$. Second, when $a \geq \frac{c}{\left(1+\frac{2k_\tau}{k_{\tau'}}\right)}$, p is jointly acceptable if it satisfies the supplier's acceptance condition (SA), i.e. $p \geq p^{SA}_{\tau,\tau'} := 2\sqrt{k_\tau a} + \frac{k_{\tau'}(c-a)}{\sqrt{k_\tau a}}$. Note that while $p^{SA}_{\tau,\tau'}$ depends on both the supplier's true type and the bank's believed type, p^{BL} depends *only* on the bank's believed type. Also, observe that $p^{BL}_{\tau'} = p^{BL}$ and $p^{SA}_{\tau,\tau'} = p^{SA}$, as presented in Section 3.4, when the bank's belief is accurate $\tau' = \tau$.

Let us consider two cases. First, when $a \geq \frac{c}{3}$. As illustrated in Figure 3.3, it is easy to verify that when the bank believes that the supplier is efficient ($\tau' = H$), p is also acceptable to the efficient (inefficient) supplier if and only if $p \geq p^{SA}_{H,H}$ ($p \geq p^{SA}_{L,H}$). By noting that $p^{SA}_{H,H} < p^{SA}_{L,H}$, we can conclude that when $p \in [p^{SA}_{H,H},\ p^{SA}_{L,H})$, p is only acceptable to the efficient supplier.

Second, for $a < \frac{c}{\left(1+\frac{2k_L}{k_H}\right)}$, both types of supplier will accept the contract if and only if $p \geq p^{BL}_{H} = \sqrt{8k_H(c-a)}$, where p depends only on the bank's belief regardless of the supplier's true type. As shown later, these properties play an important role in separating the two types of suppliers.

Figure 3.3: Illustration of Manufacturer's Payoff under Different (τ, τ')



Notes. $p^S_\tau = \arg\max_p \Pi_M(\tau, p, \tau)$ for $\tau = H,\ L$. $p^{SA}_{\tau,\tau'} = 2\sqrt{k_\tau a} + \frac{k_{\tau'}(c-a)}{\sqrt{k_\tau a}}$ for $\tau,\ \tau' = H,\ L$. The illustration is generated under the following parameters - $v = 2$, $a = 0.2$, $c = 0.4$, $k_H = 2/3$, $k_L = 1$ - so that $a < \frac{v^2}{16k_L}$.

Credible Signals under POF.

We first examine the manufacturer's choice of p_L when she faces an inefficient supplier ($\tau = L$). It is clear that if the bank also knows the supplier's type, the manufacturer should set $p_L^* = p_L^S$ to maximize her payoff. However, under asymmetric information, for p_L^S to be the equilibrium price, it also has to be a credible signal to the bank that the supplier is indeed inefficient ($\tau = L$). By comparing $\Pi_M(H, p, H)$ and $\Pi_M(H, p_L^S, L)$, it is clear that a manufacturer facing an efficient supplier ($\tau = H$) is better off by choosing from a wide range of prices different from p_L^S. Therefore, by receiving p_L^S, the bank should believe that the supplier is indeed inefficient (so that $\mu = 0$).

Lemma 3.2. *In any separating PBE, the manufacturer offers the inefficient supplier ($\tau = L$) the same contract as characterized in Proposition 3.3.1, i.e. $p_L^* = p_L^S$.*

Because p_L^S is the price that will enable the manufacturer to attain the highest payoff in the symmetric information case, Lemma 3.2 implies that information asymmetry has no negative impact on the efficiency of POF when the supplier is truly inefficient. In other words, when facing an inefficient supplier, the supplier's delivery probability and the manufacturer's payoff under POF in the asymmetric information case are identical to the those in the symmetric information case presented in Proposition 3.3.1 under POF. Combining this observation with the fact that the manufacturer's payoff is identical under both POF and BDF in the symmetric information case, we can conclude that when faced with an inefficient supplier and an information advantage, the manufacturer receives no economic benefit for offering loans to inefficient suppliers under BDF. As such, when facing an inefficient supplier, the manufacturer should let the bank handle lending under POF, even when she has an information advantage over the bank.

After settling the results for the case of the inefficient supplier ($\tau = L$), we turn the focus in this section to the efficient supplier ($\tau = H$). When the supplier is efficient, the manufacturer should offer p_H^S under symmetric information. However, in the presence of information asymmetry, p_H^S may not be the optimal choice because setting $p = p_H^S$ may not be a credible signal for the bank to believe that the supplier is indeed efficient. For example, observe from Figure 3.3 that $\Pi_M(L, p_H^S, H) > \Pi_M(L, p_L^S, L)$, that is, the manufacturer has an incentive to deceive the bank. Expecting this, the bank will not treat p_H^S as a credible signal and will not believe that the supplier's actual type is H. Therefore, in a separating equilibrium, for p_H to credibly signal that the supplier is indeed efficient, p_H has to satisfy the following manufacturer incentive (MI) compatibility constraint:

$$\Pi_M(L, p_L^S, L) \geq \Pi_M(L, p_H, H). \tag{3.10}$$

The above constraint suggests that when facing an inefficient supplier (type L), the manufacturer is better off offering p_L^S, which truthfully signals that the supplier is inefficient, rather than offering p_H to deceive the bank. In other words, for any p_H that satisfies the above constraint, the bank will believe that the supplier is type H because the manufacturer would be better off setting her contract price at p_L^S if the supplier is type L. In addition, for p_H to be an equilibrium price, it must generate more profitable for the manufacturer than any other price under the bank's belief that the supplier is inefficient, that is,

$$\Pi_M(H, p_H, H) \geq \max_{p \neq p_H} \Pi_M(H, p, L). \tag{3.11}$$

The Least-costly Separating Equilibrium when the Supplier is Efficient.

For any p_H that satisfies (3.10) and (3.11), we can conclude that this contract price is an equilibrium and can serve as a credible signal for the bank to believe that the supplier is indeed efficient ($\tau' = H$). Among all of the possible equilibria and credible contract prices p_H that satisfy (3.10) and (3.11), we now determine the least-costly separating equilibrium price p_H that maximizes the manufacturer's payoff $\Pi_M(H, p_H, H)$.[7] When facing a truly efficient supplier (type H), we can use (3.9) to formulate the manufacturer's problem as: $\max_{p_H} \Pi_M(H, p_H, H)$, subject to (3.10) and (3.11). By considering the first order condition along with the constraints, we can establish the following result:

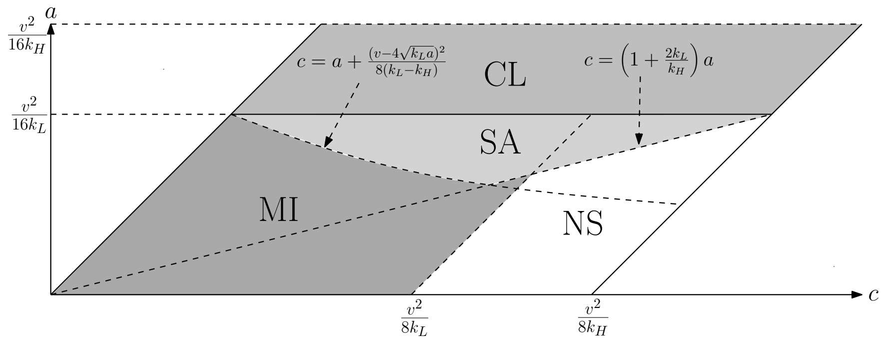
Proposition 3.5.1. *In the least-costly separating equilibrium, the price the manufacturer offers to an efficient supplier (p_H^*) is:*

1. *for* $a \geq \frac{v^2}{16k_L}$, $p_H^* = p_H^S$.
2. *for* $a < \frac{v^2}{16k_L}$ *and* $c - a \in \left(\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}, \frac{2k_L a}{k_H}\right)$, $p_H^* = p_{L,H}^{SA} - \epsilon$, *where* $\epsilon > 0$ *is an arbitrarily small quantity.*
3. *for* $c-a \in \left[0, \min\{\frac{v^2}{8k_L}, \frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}\}\right] \cup \left[\frac{2k_L a}{k_H}, \frac{v^2}{8k_L}\right]$, $p_H^* = p^{MI} := \frac{v}{2} + \sqrt{2(k_L - k_H)(c-a)} + \frac{4k_H(c-a)}{v+2\sqrt{2(k_L-k_H)(c-a)}}$.
4. *for* $c - a > \max\left\{\frac{v^2}{8k_L}, \frac{2k_L a}{k_H}\right\}$, *no separating equilibrium exists.*

Figure 3.4 illustrates the least-costly separating equilibrium, as characterized in Proposition 3.5.1. Depending on the magnitude of c and a, there are four scenarios to consider. First, consider the case where the supplier's asset value $a \geq \frac{v^2}{16k_L}$ (i.e. the "costless" Region CL, which corresponds to Region I and the top part of Region II in Figure 3.2 for $k = k_H$). In region CL, Proposition 3.5.1 suggests that the manufacturer can use p_H^S as a credible signal to make the bank believe that the supplier is indeed efficient. Because p_H^S is the optimal contract price under the symmetric information case, we can conclude that this signal is "costless" in the sense that the manufacturer can attain the highest payoff, as in the asymmetric information case. By using the same logic presented in Lemma 2, we can conclude that when faced with an efficient supplier with a high asset value $a \geq \frac{v^2}{16k_L}$,

7. It is easy to show that other separating equilibria can be eliminated by the Intuitive Criterion, which we discuss in Proposition 3.5.3.

Figure 3.4: Illustration of the Least-costly Separating Equilibrium



Notes. In Region CL, separating is *costless*. In Region SA, separating is achieved by making the *supplier's acceptance* (SA) condition binding. In Region MI, separation is achieved due to the *manufacturer's incentive* (MI) compatibility constraint. In Region NS, there is no separating equilibrium. The illustration is generated under parameters $\frac{k_L}{k_H} = 1.5$.

the manufacturer's payoff is identical under both POF and BDF: Under BDF, information advantage gives the manufacturer no economic benefit for offering loans to efficient suppliers.

Next, consider the case where the supplier's asset value a drops slightly below $\frac{v^2}{16k_L}$ (Region SA in Figure 3.4). In this case, we can check from Figure 3.3 (which satisfies $a < \frac{v^2}{16k_L}$) that $p_H^S > p_{L,H}^{SA}$, which implies that the truly inefficient type-L supplier will accept the price p_H^S if the bank believes the supplier is efficient (type H). Also, by noting from Figure 3.3 that $\Pi_M(L, p_H^S, H) > \Pi_M(L, p_L^S, L)$, the contract price p_H^S is no longer credible because the bank knows that the manufacturer has an incentive to deceive the bank (i.e. it violates the incentive compatibility constraint (3.10)). Therefore, in order to send a credible signal to the bank that the supplier is indeed efficient (type H), the manufacturer should set the contract price $p_H^* = p_{L,H}^{SA} - \epsilon$ so that the inefficient (type-L) supplier will not accept when the bank believes the supplier is type H. However, this strategy is no longer effective if a becomes very low as the deviation will be too large, making it either unacceptable for even the efficient supplier, i.e. when $c > \left(1 + \frac{2k_L a}{k_H}\right) a$, or unprofitable for the manufacturer to signal, i.e. when $c < a + \frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}$.

As a drops further, the strategy adopted by the manufacturer bifurcates. Consider the case where $c-a<\frac{v^2}{8k_L}$ (i.e. the Region MI under which the incentive constraints (3.10) and (3.11) are satisfied). Specifically, it can be shown that p^{MI} is the unique price that satisfies both (3.10) and (3.11).[8]

Finally, let us consider the case where $c-a>\max\left\{\frac{v^2}{8k_L},\frac{2k_La}{k_H}\right\}$ (Region NS, "no separating"). Recall that a separating equilibrium exists only if the manufacturer can find a price p_H such that (3.10) holds. However, it is easy to check from Figure 3.2 that the manufacturer should not source from an inefficient supplier with cost factor $k=k_L$ under symmetric information, i.e. $\Pi_M(L,p_L^S,L)=0$. Therefore, any p_H that satisfy (3.10) must have $\Pi_M(L,p_H,H)=0$. As $c>\frac{2k_La}{k_H}$, such p_H should also lead to $\Pi_M(H,p_H,H)=0$, deeming it unacceptable to the efficient supplier ($\tau=H$). Therefore, a separating equilibrium does not exist.

In summary, we find that when facing an efficient supplier (type H) with a high asset level $a\geq\frac{v^2}{16k_L}$, the manufacturer can set her separating price $p_H^*=p_H^S$ to create a credible signal to the bank that the supplier is indeed efficient. Also, the separating equilibria for this case are costless, and hence, BDF generates no economic benefit over POF, even when the manufacturer has an information advantage. For the case of an efficient supplier (type H), we find that the manufacturer can create a credible signal by setting her separating price p_H^* when the supplier's asset value is not too low (Regions SA and MI). However, when the efficient supplier's asset value is low and the production cost is high (i.e. $(c-a)$ exceeds a certain threshold), we find that the manufacturer can no longer create a credible signal that is also profitable, and therefore, no separating price can exist.

8. In fact, when $p_H=p^{MI}$, both (3.10) and (3.11) are binding. This suggests that while the manufacturer has no incentive to offers an inefficient supplier p^{MI} (3.10), she is also indifferent about either signaling the true type or having the supplier identified as being inefficient. Therefore, the manufacturer does not actually benefit from separating. As shown in Proposition 3.5.3, the separating equilibrium Region MI will be eliminated by the Intuitive Criterion.

3.5.3 Pooling Equilibria

In the last subsection, we show that a separating equilibria is costless and the manufacturer can set $p_H^* = p_H^S$ when the supplier's asset level $a \geq \frac{v^2}{16k_L}$. Because separating equilibria dominate all pooling equilibria when we apply the Intuitive Criterion eliminates, it suffices to focus on pooling equilibria for the case where $a < \frac{v^2}{16k_L}$.

In a pooling equilibrium, for any price p_W and interest rate $i_{B,W}$, a type-τ supplier's best response e_τ^* is given in (3.7), with p being replaced by p_W and i_B, by $i_{B,W}$. Also, in a pooling equilibrium, the manufacturer sets the same price p_W regardless of the supplier's type. As such, the signal p_W is uninformative, meaning that the bank's posterior belief remains the same as its prior, i.e. $\mu = \lambda$. In this case, by using the supplier's best response e_τ^* and the fact that the bank will set its interest rate $i_{B,W}$ to break even in expectation and by considering the probability distribution of k so that $k = k_H$ with probability λ and $k = k_L$ with probability $(1 - \lambda)$, we can use the same approach as presented in Section 3.3 to show that the bank's equilibrium interest rate $i_{B,W}^*$ for any pooling equilibrium p_W will satisfy:

$$i_{B,W}^* = \frac{p_W - \sqrt{p_W^2 - 8k_W(c-a)}}{2c} + \frac{a}{c} - 1, \tag{3.12}$$

where $k_W := \left(\frac{1-\lambda}{k_L} + \frac{\lambda}{k_H}\right)^{-1}$, which can be interpreted as the cost factor of the weighted average supplier. Plugging p_W and $i_{B,W}^*$ into (3.7), and then the resulting e_W^* into (3.9), we can determine the manufacturer's payoff under pooling equilibria as:

$$\Pi_M(\tau, p_W, W) = \frac{p_W + \sqrt{p_W^2 - 8k_W(c-a)}}{4k_\tau}(v - p_W) \cdot \mathbb{1}_{\left\{p_W + \sqrt{p_W^2 - 8k_W(c-a)} \geq 4\sqrt{k_\tau a}\right\}}. \tag{3.13}$$

By analyzing $\Pi_M(\tau, p_W, W)$, $\tau = H, L\}$, we can obtain the following results.

Proposition 3.5.2. *When the supplier's asset value $a < \frac{v^2}{16k_L}$, the Pareto-dominating pooling equilibrium can be characterized as follows:*

1. *When $c - a \leq \frac{v^2}{8k_W}$, the manufacturer sets $p_W^* = \frac{v}{2} + \frac{4k_W(c-a)}{v}$ for both types of suppliers.*

2. *When $c - a > \frac{v^2}{8k_W}$, the manufacturer does not source from any supplier.*

In the pooling equilibrium, Proposition 3.5.2 asserts that regardless of the supplier type, the manufacturer's sourcing decision and contract price p_W depend on $k_W = \left(\frac{1-\lambda}{k_L} + \frac{\lambda}{k_H}\right)^{-1}$, which is a function of not only k_H but also k_L and λ. Specifically, we can use the fact that k_W is increasing in k_L and decreasing in λ so that the condition is more likely to hold for the second statement. As such, we can interpret the second statement as follows. First, when the inefficient supplier's (type-L) cost factor k_L is very high, it is more likely that the manufacturer will not source from any supplier in a pooling equilibrium. Second, when the market consists predominantly of inefficient suppliers (so that λ is small), it is more likely that the manufacturer will not source from any supplier in a pooling equilibrium. In these two cases, the pooling equilibrium does not exist.

For the case where the pooling equilibrium exists as stated in the first statement, we can substitute p_W^* into (3.12) and (3.7) to determine the supplier's delivery probability $e_\tau^*(p_W^*, i_B^*)$ associated with the pooling equilibrium. While the pooling equilibrium contract price p_W^* deviates from the optimal contract price stated in Proposition 1 for each type of supplier under symmetric information, it is interesting to note that $e_\tau^*(p_W^*, i_B^*) = e_\tau^*$ for each type of supplier τ under symmetric information. This observation implies that even though the manufacturer's profitability under POF in the pooling equilibrium is sacrificed due to information asymmetry, the supplier's delivery probability remains the same as in the symmetric information case.

3.5.4 Equilibria Refinement

By comparing Propositions 3.5.1 and 3.5.2, we notice that for some regions of (c, a), both separating and pooling equilibria exist. To identify the stable dominant equilibrium, we employ the Intuitive Criterion Cho and Kreps (1987) and obtain the following results.

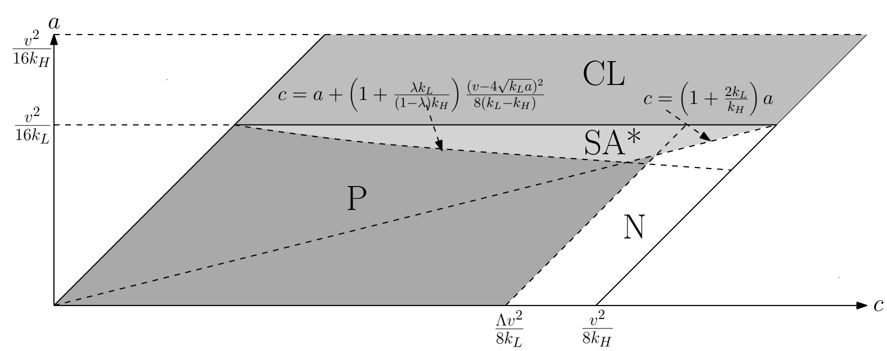
Proposition 3.5.3. *In the signaling game associated with POF, the dominant equilibrium for the case where the supplier's asset value* $a < \frac{v^2}{16k_L}$ *can be characterized as follows:*

1. *When* $c - a \in \left[\left(1 + \frac{\lambda k_L}{(1-\lambda)k_H}\right)\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)},\ \left(\frac{2k_L}{k_H}\right)a\right]$, *only the least-costly separating equilibrium survives the Intuitive Criterion. In equilibrium, the manufacturer offers* $p^{SA}_{L,H} - \epsilon$ *to the efficient supplier and* p^S_L *to the inefficient one.*

2. *When* $c - a \in \left(0,\ \left(1 + \frac{\lambda k_L}{(1-\lambda)k_H}\right)\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}\right) \cup \left(\left(\frac{2k_L}{k_H}\right)a,\ \frac{v^2}{8k_W}\right)$, *only the Pareto-dominating pooling equilibrium survives the Intuitive Criterion. In equilibrium, the manufacturer offers* $p^*_W = \frac{v}{2} + \frac{4k_W(c-a)}{v}$ *to both types of supplier.*

3. *When* $c - a > \max\left\{\left(\frac{2k_L}{k_H}\right)a,\ \frac{v^2}{8k_W}\right\}$, *the manufacturer does not source from either type of supplier.*

Figure 3.5: Dominant PBE that Survives the Intuitive Criterion



Notes. In Region CL, separating is *costless*. In Region SA^*, the separating equilibrium with a binding supplier's acceptance condition survives the Intuitive Criterion. In Region P, the pooling equilibrium survives the Intuitive Criterion. In Region N, the manufacturer sources from neither type of supplier. The illustration is generated using $\frac{k_L}{k_H} = 1.5$ and $\lambda = 0.5$.

Figure 3.5 illustrates the three scenarios characterized in Proposition 3.5.3, together with the costless separating equilibrium as established in Proposition 3.5.1. Compared with Figure 3.4, the dominant separating equilibrium is eliminated by the Intuitive Criterion for all of Region MI and part of Region SA as the manufacturer's payoff in the pooling equilibrium is higher than that of the separating equilibrium whether the supplier is efficient or not, i.e. $\Pi_M(\tau, p_W^*, W) > \Pi_M(\tau, p_H^*, \tau)$ for $\tau = H, L$. On the other hand, for the remaining part of Region SA (Region SA^* in Figure 3.5), the Intuitive Criterion eliminates the pooling equilibrium. The reason is as follows. First, observe from Proposition 3.5.1 that when the manufacturer sets her contract price at $p_{L,H}^{SA} - \epsilon$, it sends a credible signal to the bank so that the bank will believe that the supplier is efficient (type H). Second, it can be shown that $\Pi_M(H, (p_{L,H}^{SA} - \epsilon), H) > \Pi_M(H, p_W^*, W)$ for (c, a) in Region SA^*. Therefore, the manufacturer has the incentive to deviate from the pooling equilibrium p_W^* to the separating equilibrium $p_{L,H}^{SA} - \epsilon$. These two observations imply that the separating equilibrium $(p_{L,H}^{SA} - \epsilon)$ dominates the pooling equilibrium in Region SA^*.

3.5.5 Comparing POF and BDF under Information Asymmetry

Armed with the stable dominant equilibria associated with the signaling game under POF as stated in Proposition 3.5.3, we now examine the conditions under which BDF is more appealing than POF when the manufacturer has an information advantage over the bank. Recall that as the bank is not involved under BDF, information asymmetry has no impact on the manufacturer's payoff under BDF. Hence, the manufacturer's payoff under BDF is given in Proposition 3.4.1, which is identical to that under POF as presented in Proposition 3.3.1. Therefore, BDF is more appealing than POF in the asymmetric information case when the manufacturer incurs a certain cost for sending credible signals under POF due to information asymmetry. Recall from Proposition 3.5.3 that when facing an inefficient supplier, the manufacturer is not adversely influenced by information asymmetry. Therefore, it suffices to focus our discussion on the case where the supplier is efficient. Such a focus is also supported by anecdotal evidence that many manufacturers only offer BDF to suppliers with a good track record.

When faced with an efficient supplier ($\tau = H$), Proposition 3.5.3 reveals that the manufacturer may need to bear certain costs under POF due to information asymmetry. Therefore, the higher the signal cost the manufacturer has to bear under POF when she has private information, the more appealing BDF will be. According to the optimal contract characterized in Propositions 3.5.1 and 3.5.3, we discuss the following two scenarios.

In the first scenario, the supplier's asset value is high so that $a \geq \frac{v^2}{16k_L}$. In this case, Proposition 3.5.1 asserts that the manufacturer can send a "costless" and credible signal to the bank under POF so that the manufacturer will obtain the same payoff as if there was no information asymmetry. Consequently, the manufacturer will obtain the same payoff under both POF and BDF.

In the second scenario, the supplier's asset value is low, i.e. $a < \frac{v^2}{16k_L}$. In this scenario, possessing private information about the supplier imposes additional costs on the manufacturer. An extreme case is in Region N, as depicted in Figure 5, where the manufacturer fails to source from the efficient supplier if she relies on POF. By considering the third statement in Proposition 3.5.3 and the aforementioned properties of k_W, we can see that Region N becomes larger as the manufacturer's outside option becomes more expensive (larger v), the average efficiency of the supplier becomes lower (lower λ), or the supply market becomes more heterogeneous (higher k_L or lower k_H). Under these scenarios, BDF, which does not bear such costs associated with information asymmetry, should be a more appealing financing option than POF.

Finally, when (c, a) falls in Regions SA^* or P, the first and second statements in Proposition 3.5.3 suggest that while POF remains a feasible option, the manufacturer needs to bear additional costs, either because it is costly for her to send a credible signal to the bank that the supplier is efficient ($\tau = H$) in the separating equilibrium or she has to compensate the supplier for the higher interest rate charged by the bank as it assumed the supplier is of average efficiency. To quantify this cost when (c, a) is in Regions SA^* or P, let Δ_M be the difference between the manufacturer's payoff (Π_M) under symmetric information (Proposition 3.3.1) and that under asymmetric information (Proposition 3.5.3). It is clear that $\Delta_M > 0$. Also, the higher the value of Δ_M, the more appealing BDF becomes. The following corollary examines the impact of various factors on Δ_M:

Corollary 3.5.1. *For (c, a) in Regions SA^* and P, Δ_M decreases in the supplier's asset value a and the supplier's cost factor k_H and (weakly) decreases in the percentage of efficient suppliers in the market λ. However, Δ_M (weakly) increases in the manufacturer's outside option v.*

Combining the results as stated in Corollary 3.5.1 for the case where (c, a) falls in Regions SA^* and P with the discussion above, where (c, a) falls in Regions CL and N, we can examine the impact of various factors on the relative attractiveness of BDF as follows. First, BDF is more beneficial for the manufacturer when the supplier's asset value a is low. Therefore, manufacturers should offer financial help to a supplier when the value of the supplier's assets shrinks, such as during an economic downturn. This result provides a plausible explanation for the emergence of BDF during financial crises. For example, during the Asian Financial Crisis in 1998, Li & Fung offered direct financing to their cash-strapped suppliers in Indonesia (Tang (2006)).

Second, BDF is more appealing to the manufacturer when the efficient supplier's cost factor k_H is low, i.e. when the supplier is more efficient. Therefore, the manufacturer should opt to offer loans to suppliers who need help with acquiring new equipment to improve their operational efficiency.

Third, BDF is more valuable to the manufacturer when the market consists of mostly inefficient suppliers (i.e. when λ is low). For example, when (c, a) falls in Region P, i.e. the pooling equilibrium is the stable dominant one, when λ is low, k_W becomes larger, resulting in either the manufacturer offering a higher contract price p_W^* or her not sourcing from the supplier (i.e. when $k_W > \frac{v^2}{8(c-a)}$). This observation implies that BDF can be an effective financing scheme for manufacturers who source from developing countries comprising predominantly inefficient suppliers.

Finally, the manufacturer has more incentive to offer BDF when her outside option v becomes more expensive. When v is larger, we can see from Figure 3.5 that Regions SA^*, P, and N expand. Furthermore, Proposition 3.5.3 reveals that under POF, it is more likely that the manufacturer will incur signaling costs or not source from the supplier. As such, BDF becomes more appealing to the manufacturer. This observation suggests that BDF should be more used more often when the supplier is more specialized and the alternative sourcing option is particularly expensive (i.e. when v is high). Consistent with the anecdotal evidence, manufacturers that work with specialized suppliers, such as such as Rolls Royce and GSK, are among the pioneers of directly financing suppliers under BDF.

3.6 Conclusions

POF and BDF are both relatively new financing schemes that aim to help financially constrained suppliers obtain the financing to start production. Different from more traditional financing means such as asset-based loans and factoring, which are secured by tangible assets, repayment under both POF and BDF hinges on successful delivery by the supplier. As such, the efficiency of the two schemes depends crucially on control over and knowledge of the supplier's performance risk.

By using a three-party model that captures the interaction between a manufacturer, a supplier, and a bank, we find that under symmetric information between the manufacturer and bank, BDF and POF are equivalent in terms of the supplier's delivery probability in equilibrium and the manufacturer's payoff. This result implies that when facing supply risk, the additional lever of interest rates does not mitigate the supplier's moral hazard beyond what the contract price can achieve.

While the manufacturer's control advantage does not translate directly into an advantage of BDF, there is an advantage for the manufacturer when she has access to more information than the bank, especially when the supplier is extremely financially constrained. When the supplier's asset level is not too low, the manufacturer can signal her private information about the supplier to the bank through the sourcing contract without incurring an additional cost, meaning that POF is as efficient in this case as under the symmetric information case. On the other hand, when the supplier's asset level is low, signaling private information under POF becomes too costly for the manufacturer, if not impossible. We also find that BDF is more attractive when the manufacturer's outside option is expensive, the average efficiency of the supplier is low, or the heterogeneity of suppliers is high. Our finding that the advantage of BDF is more likely to be related to the manufacturer's information advantage is consistent with anecdotal evidence that BDF is more commonly observed in developing countries or where manufacturers deal with specialized suppliers. By contrast, in industries where buyers do not necessarily possess more accurate information about suppliers than banks, such as when a retailer orders from a new supplier for the first time, POF may still be an attractive financing scheme; this is also consistent with anecdotal evidence (Tice (2010)).

As the first attempt at understanding the relative efficiency of POF and BDF, this chapter is not without limitations. For example, due to data availability, our results are related only to anecdotal evidence. However, should data become available, empirical research may be conducted to verify the various predictions the paper generates.

APPENDIX A

THE EXAMPLE IN SUBSECTION 2.2

Suppose an economy with 2 regions (A and B) and 3 potential future states with equal probability ($Prob\,(S = S_i) = \frac{1}{3}$, $\forall i \in \{1, 2, 3\}$):

S_1: both A and B function;

S_2: A cannot produce and B can;

S_3: B cannot produce and A can.

Next, suppose we have 4 firms in the economy, 3 manufacturers and 1 distributer. For the manufacturers, it is limited in production capacity, and it produces a payoff of 1 (due to fixed production capacity) as long as one of their input region function. Firm 1, 2, and 3 are manufacturers. Firm 1 only sources input from region A, Firm 2 only sources input from region B, and Firm 3 sources from both regions. Firm 4 is the distributor, it connects to both region A and region B with a fixed cost of 1 in all states. Therefore, in each of the states mentioned above, the payoff for these 4 firms are below:

$\Pi_1 = \{1, 0, 1\}$, $\Pi_2 = \{1, 1, 0\}$, $\Pi_3 = \{1, 1, 1\}$, $\Pi_4 = \{1, 0, 0\}$.

Let Ω denote the covaraince matrix for the firms' payoffs. Then we have

$$\Omega = \begin{bmatrix} \frac{1}{3} & -\frac{1}{6} & 0 & \frac{1}{6} \\ -\frac{1}{6} & \frac{1}{3} & 0 & \frac{1}{6} \\ 0 & 0 & 0 & 0 \\ \frac{1}{6} & \frac{1}{6} & 0 & \frac{1}{3} \end{bmatrix} \tag{A.1}$$

Suppose we have a representative mean-variance investor, and let $\mu = [\mu_1, \mu_2, \mu_3, \mu_4]$ denote firms expected return. Then for any feasible returns $\tilde{\mu}$ the investor targets, the investor find the portfolio weights $w = [w_1, w_2, w_3, w_4]$ by solving

$$\min_{w} w^{'}\Omega w$$
$$s.t. w^{'}\mu = \tilde{\mu}, w^{'}1 = 1$$

By differentiating the Lagrangian with respect to w we get $\Omega w - \lambda_1\mu - \lambda_2 1 = 0$. The symmetry of firm 1 and firm 2 gives $w_1 = w_2$ and $\mu_1 = \mu_2$. By plugging in the values, we have

$$\begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \end{bmatrix} = \frac{1}{\lambda_1} \begin{bmatrix} \frac{1}{6}w_1 + \frac{1}{6}w_4 \\ \frac{1}{6}w_1 + \frac{1}{6}w_4 \\ 0 \\ \frac{1}{3}w_1 + \frac{1}{3}w_4 \end{bmatrix} + \frac{\lambda_2}{\lambda_1}$$

Therefore, it is clear that $\mu_3 < \mu_1 = \mu_2 < \mu_4$, i.e. the manufacturers have lower risk than the distributor, and the dual sourcing manufacturer is less risky than the single sourcing manufacturer. This relationship is shown in our empirical result of the second order effect.

APPENDIX B

FAMA-MACBETH REGRESSION

OLS standard errors are uncorrelated when the residuals are independently and identically distributed (i.i.d.). When the residuals are correlated across observations, OLS standard errors can be biased and either over or underestimate the true variability of the coefficient estimates. The residuals of a given firm may have time series dependence for a given firm, which is called unobserved firm effect. Alternatively, the residuals of a given year may have cross-sectional dependence, which is called unobserved time effect. In the model specification of the first-order effect, we have defined $r_{i,t}$ as the return of firm i in month t, which is a linear combination of its own one-month lagged effect, weighted sum of supplier and customer one-month lagged effect, weighted sum of supplier and customer returns, as well as its own idiosyncratic shocks:

$$r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 \sum_j w_{ij}^{in} r_{j,t-1} + \beta_3 \sum_j w_{ij}^{out} r_{j,t-1} + \beta_4 \sum_j w_{ij}^{in} r_{j,t} + \beta_5 \sum_j w_{ij}^{out} r_{j,t} + \epsilon_{i,t}. \tag{B.1}$$

Since most time series correlation has been captured by the one-month lagged effects, and we have found trailing horizons of more than two months have insignificant effect on current returns, the model specification have little unobserved firm effect in the residuals after controlling for the one-month lagged effects. Therefore, we should focus on the unobserved time effect, thus we choose Fama-MacBeth regression to correct the possible biased estimate in OLS. Fama-MacBeth regression is first proposed by Fama and MacBeth (1973), and it is the most commonly used solution to the time effect in asset pricing literature. A detailed discussion of Fama-MacBeth regression versus other solutions such as clustered standard errors is given in Petersen (2009).

The Fama-MacBeth method estimates the loadings on risk factors in two steps to avoid problems of correlation across contemporaneous residuals in panel data. The first step runs T cross sectional regressions to get T estimates coefficients for assets, while the second step uses the average of the T estimated coefficients to find the loading estimates, which is below.

$$\hat{\beta}_{FM} = \sum_{t=1}^{T} \frac{\hat{\beta}_t}{T} \tag{B.2}$$

$$= \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{t=1}^{N} X_{it} Y_{it}}{\sum_{t=1}^{N} X_{it}^2} \right) \tag{B.3}$$

$$= \beta + \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{i=1}^{N} X_{it} \epsilon_{it}}{\sum_{i=1}^{N} X_{it}^2} \right) \tag{B.4}$$

and the estimated variance of the Fama-MacBeth estimate is calculated as

$$S^2 \left(\hat{\beta}_{FM} \right) = \frac{1}{T} \sum_{t=1}^{T} \frac{\left(\hat{\beta}_t - \hat{\beta}_{FM} \right)^2}{T-1} \tag{B.5}$$

The variance formula requires that cross sectional estimates of the coefficients are independent of each other, i.e. there is no firm effect. Since our model specification have little unobserved firm effect, Fama-MacBeth regression is a good solution to treat the unobserved time effect in the model, and should yield unbiased estimate.

Fama-MacBeth regression is used in the empirical tests of the first-order effects. Below is the complete Table 5 in the paper, including loadings on the common factors.

Table B.1: Fama-MacBeth Regression after Controlling for Common Factors.

This table summarizes the Fama-Macbeth results after controlling for common asset pricing factors. It is the complete table 5 in the paper. †.

$$\begin{aligned} r_{i,t} &= \alpha + \beta_1 r_{i,t-1} + \beta_2 \sum_j w_{ij}^{in} r_{j,t-1} + \beta_3 \sum_j w_{ij}^{out} r_{j,t-1} + \beta_4 \sum_j w_{ij}^{in} r_{j,t} + \beta_5 \sum_j w_{ij}^{out} r_{j,t} \\ &+ b_i \left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + u_i MOM_t + \epsilon_{it} \end{aligned}$$

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$	$R_{mt} - R_{ft}$	SMB_t	HML_t	MOM_t
Ave. Coef	-0.000	-0.086***	0.063***	0.010	0.111***	0.503*	0.007 ***	0.006***	-0.001	-0.002***
(T-Stat)	(-0.45)	(-9.16)	(3.42)	(0.23)	(4.28)	(1.78)	(14.71)	(7.06)	(-1.41)	(-4.22)
Ave. Coef	-0.001	-0.091***	0.050***	0.029			0.011 ***	0.007***	-0.000	-0.002***
(T-Stat)	(-1.09)	(-10.43)	(3.02)	(0.70)			(33.17)	(8.58)	(-0.68)	(-6.19)
Ave. Coef	-0.002*	-0.054***					0.011***	0.006***	-0.000	-0.002***
(T-Stat)	(-1.80)	(-7.93)					(37.58)	(8.11)	(-0.74)	(-5.22)
Ave. Coef	-0.001		0.029**				0.011***	0.007***	-0.001	-0.002***
(T-Stat)	(-1.60)		(2.29)				(34.70)	(9.30)	(-1.57)	(-6.84)
Ave. Coef	-0.002**			0.034*			0.011***	0.006***	-0.001	-0.002***
(T-Stat)	(-2.50)			(2.05)			(36.27)	(7.98)	(-1.16)	(-6.42)
Ave. Coef	-0.001**				0.126***		0.010***	0.005***	-0.001	-0.002***
(T-Stat)	(-1.75)				(6.24)		(28.19)	(7.30)	(-1.38)	(-4.94)
Ave. Coef	-0.002***					0.501*	0.009***	0.006***	-0.001	-0.002***
(T-Stat)	(-2.83)					(1.69)	(23.57)	(7.72)	(-1.08)	(-5.72)
Ave. Coef	-0.001		0.029**		0.130***		0.009***	0.006***	-0.001	-0.002***
(T-Stat)	(-0.886)		(2.14)		(5.93)		(24.89)	(8.12)	(-1.80)	(-5.36)
Ave. Coef	-0.003***			0.041		0.492**	0.009***	0.006***	-0.001	-0.002***
(T-Stat)	(-2.91)			(1.66)		(2.19)	(22.53)	(7.17)	(-1.20)	(-5.67)
Ave. Coef	-0.002***				0.114***	0.485*	0.008***	0.005***	-0.001	-0.001***
(T-Stat)	(-2.16)				(5.45)	(1.79)	(18.30)	(6.57)	(-1.37)	(-4.36)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results after controlling for common asset pricing factors. We have similar results to those in Table 4. The results are consistent for both univariate and multivariate cases. All factors are defined by self-financing portfolio. Factor data is from the Kenneth French data library.

APPENDIX C

ROBUSTNESS TEST ON INVESTOR INATTENTION

Although the results such as the supplier lagged effect are consistent with the investor's limited attention hypothesis, there are a number of other plausible explanations of the data. This section shows results for a series of robustness tests for investor inattention.

As discussed in Chapter 1, a number of papers find that larger firms, or firms with higher levels of analyst coverage, institutional ownership, and trading volume, lead smaller firms or firms with lower levels of analyst coverage, institutional ownership, and trading volume. The supplier lag effect results could be caused by firms of different size, analyst coverage, institutional ownership, and trading volume. To ensure that our results are not driven by those alternative explanations, we conduct the following robustness tests.

To control for the firm size difference, we only pick the firms that have their market capitalization larger than the input supplier weighted firms' market capitalization, i.e.

$$ME_i > \sum_j w_{ij}^{in} ME_j \tag{C.1}$$

In other words, the firms we pick are all larger firms compared to their average supplier firms weighted by their purchase orders. Since smaller supplier firms are less noticeable to investors, then if we still see supplier lagged effect this should due to other reasons than the firm sizes. In Table C.1, we see the supplier lag effect still exists. Actually, since what are left after the filtering are relatively larger firms, their supply chain relationships captured by SPLC are more likely to represent their actual supply chain position, the lag effect becomes even stronger by comparing the t-statistics with those without filtering out any firms.

To control for the institution ownership, we only pick those firms that have their institution ownership ratio larger than the input supplier weighted institution ownership ratio,

Table C.1: Fama-MacBeth Regression Controlling Market Capitalization

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	0.065***	-0.091***	0.070**	0.025	0.391***	0.370***
(T-Stat)	(6.29)	(-5.99)	(2.77)	(0.88)	(15.18)	(12.92)
Ave. Coef	0.014***	-0.103***	0.105***	0.045		
(T-Stat)	(14.87)	(-5.21)	(3.14)	(1.27)		
Ave. Coef	0.014***	-0.031**				
(T-Stat)	(18.15)	(-2.56)				
Ave. Coef	0.014***		0.047***			
(T-Stat)	(18.45)		(3.07)			
Ave. Coef	0.013***			0.031*		
(T-Stat)	(18.27)			(1.97)		
Ave. Coef	0.008***				0.589***	
(T-Stat)	(10.40)				(24.38)	
Ave. Coef	0.006***					0.650***
(T-Stat)	(6.09)					(22.14)
Ave. Coef	0.009***		0.032**		0.593***	
(T-Stat)	(10.52)		(2.14)		(24.32)	
Ave. Coef	0.006***			0.021		0.656***
(T-Stat)	(5.68)			(1.321)		(21.951)
Ave. Coef	0.006***				0.388***	0.373***
(T-Stat)	(6.42)				(15.89)	(13.19)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results of the regression (1) using concurrent returns and one-month lagged effect as independent variables. Since we want to test whether the robustness of whether larger suppliers affect the supplier lag effect, the firms are chosen so that supplier's ME < firm's ME.

i.e.

$$\left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in}\left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_j \tag{C.2}$$

In other words, the firms we pick are owned less than their average supplier firms by the institutions. Institution ownership data is from Thomson-Reuters Institutional Holdings (13F) Database [1]. The result is shown in Table C.2, still the supplier lagged effect persists.

To control for the analyst coverage, we only pick those firms that have their number of analyst forecast larger than the input supplier weighted number of analyst forecast, i.e.

$$AnalystForecastCount_i > \sum_j w_{ij}^{in} AnalystForecastCount_j \tag{C.3}$$

In other words, the firms we pick have higher analyst coverage than their average supplier firms. Analyst coverage data is from the IBES dataset. The average number of analyst forecast as of June 30, 2013 is 7.84, with Apple and Intel have largest number of analyst forecasts, 56 and 45 respectively. About 49.49% firms in the SPLC universe are not covered by any analyst forecast at all. The result is shown in Table C.3, again the supplier lagged effect persists.

Lastly, to control for the trading volume, we only pick those firms that have their trading volume turnover rate larger than the input supplier weighted turnover rate, i.e.

$$\left(\frac{TradingVolume}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in}\left(\frac{TradingVolume}{TotalShareOutstanding}\right)_j \tag{C.4}$$

1. http://www.whartonwrds.com/archive-pages/our-datasets/thomson-reuters-2/#sthash.V7aCJYVw.dpuf

Table C.2: Fama-MacBeth Regression Controlling Institution Ownership

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	0.002*	-0.090***	0.084***	0.027	0.414***	0.566***
(T-Stat)	(1.77)	(-6.84)	(3.45)	(0.79)	(13.14)	(14.07)
Ave. Coef	0.013***	-0.101***	0.119***	-0.003		
(T-Stat)	(10.09)	(-5.71)	(3.89)	(-0.08)		
Ave. Coef	0.013***	-0.041**				
(T-Stat)	(10.85)	(-3.71)				
Ave. Coef	0.013***		0.048**			
(T-Stat)	(11.57)		(2.53)			
Ave. Coef	0.012***			0.029		
(T-Stat)	(11.36)			(1.15)		
Ave. Coef	0.006***				0.631***	
(T-Stat)	(5.67)				(23.87)	
Ave. Coef	0.001					0.857***
(T-Stat)	(0.98)					(24.96)
Ave. Coef	0.008***		0.046**		0.636***	
(T-Stat)	(6.44)		(2.54)		(23.57)	
Ave. Coef	0.001			0.031		0.861***
(T-Stat)	(0.98)			(1.23)		(24.65)
Ave. Coef	0.002				0.414***	0.560***
(T-Stat)	(1.56)				(13.84)	(15.49)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results of the regression (1) using concurrent returns and one-month lagged effect as independent variables. Since we want to test whether the robustness of whether suppliers of higher institution ownership affect the supplier lag effect, the firms are chosen so that $\left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in} \left(\frac{InstitutionOwnedShares}{TotalShareOutstanding}\right)_j$.

Table C.3: Fama-MacBeth Regression Controlling Analyst Coverage

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	-0.000	-0.081***	0.047**	-0.007	0.377***	1.024*
(T-Stat)	(-0.11)	(-6.49)	(2.25)	(-0.17)	(16.15)	(1.89)
Ave. Coef	0.008***	-0.077***	0.071***	-0.067		
(T-Stat)	(7.94)	(-4.95)	(2.90)	(-0.75)		
Ave. Coef	0.008***	-0.035**				
(T-Stat)	(8.48)	(-3.48)				
Ave. Coef	0.008***		0.032**			
(T-Stat)	(8.70)		(2.19)			
Ave. Coef	0.008***			-0.12		
(T-Stat)	(8.34)			(-0.88)		
Ave. Coef	0.003***				0.590***	
(T-Stat)	(3.46)				(28.88)	
Ave. Coef	-0.001					1.230**
(T-Stat)	(-0.73)					(2.51)
Ave. Coef	0.004***		0.027*		0.595***	
(T-Stat)	(4.07)		(1.88)		(28.73)	
Ave. Coef	-0.001			-0.016		1.243***
(T-Stat)	(-0.74)			(-0.55)		(2.50)
Ave. Coef	-0.000				0.374***	1.001*
(T-Stat)	(-0.457)				(17.03)	(1.92)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results of the regression (1) using concurrent returns and one-month lagged effect as independent variables. Since we want to test whether the robustness of whether suppliers covered more by analysts affect on the supplier lag effect, the firms are chosen so that $AnalystForecastCount_i > \sum_j w_{ij}^{in} AnalystForecastCount_j$.

In other words, the firms we pick are traded more frequently than their average supplier firms. Share trading volume data comes from the CRSP dataset. The supplier lagged effect does not disappear based on the results in Table C.4.

Table C.4: Fama-MacBeth Regression Controlling Trading Volume

	α	$r_{i,t-1}$	$\sum_j w_{ij}^{in} r_{j,t-1}$	$\sum_j w_{ij}^{out} r_{j,t-1}$	$\sum_j w_{ij}^{in} r_{j,t}$	$\sum_j w_{ij}^{out} r_{j,t}$
Ave. Coef	0.000	-0.081***	0.054**	0.060	0.429**	0.887***
(T-Stat)	(0.30)	(-7.94)	(2.53)	(0.17)	(17.39)	(2.41)
Ave. Coef	0.010***	-0.081***	0.087***	-0.045		
(T-Stat)	(8.56)	(-6.32)	(3.45)	(-0.69)		
Ave. Coef	0.009***	-0.038**				
(T-Stat)	(8.70)	(-4.42)				
Ave. Coef	0.009***		0.031*			
(T-Stat)	(9.13)		(1.96)			
Ave. Coef	0.009***			-0.08		
(T-Stat)	(9.05)			(-0.85)		
Ave. Coef	0.004***				0.653***	
(T-Stat)	(3.54)				(29.66)	
Ave. Coef	-0.002					1.158***
(T-Stat)	(-1.54)					(3.48)
Ave. Coef	0.005***		0.658***		0.026*	
(T-Stat)	(4.40)		(29.06)		(1.77)	
Ave. Coef	-0.001			1.166***		-0.009
(T-Stat)	(-1.20)			(3.45)		(-0.36)
Ave. Coef	-0.001				0.424***	0.882**
(T-Stat)	(-0.909)				(19.05)	(2.49)

*p-value<10%, **p-value<5%, ***p-value<1%

Notes. This table summarizes the Fama-MacBeth results of the regression (1) using concurrent returns and one-month lagged effect as independent variables. Since we want to test whether the robustness of whether suppliers traded more frequently affect on the supplier lag effect, the firms are chosen so that $\left(\frac{TradingVolume}{TotalShareOutstanding}\right)_i > \sum_j w_{ij}^{in} \left(\frac{TradingVolume}{TotalShareOutstanding}\right)_j$.

APPENDIX D

PROOFS FOR CHAPTER 3

Proof. Proof of Lemma 3.1. In a centralized control system, the system's payoff is $v - [(1-e)v + c + ke^2]$, which is maximized at $e = \frac{v}{2k}$. The corresponding optimal payoff is $\frac{v^2}{4k} - c$. For the centralized system to be viable, the optimal payoff has to be non-negative, i.e. $\frac{v^2}{4k} \geq c$, as desired. □

Proof. Proof of Proposition 3.3.1. We prove the results by using e as the decision variable. Using (3.4) to express p in terms of e, we have $p = 2ke + \frac{c-a}{e}$. By substituting p using the above formula into the manufacturer's payoff (3.9) as well as the constraints $p \geq p^{BL}$ and $p \geq p^{SA}$, the manufacturer's optimization problem becomes:

$$\max_e \ \Pi_M = ev - 2ke^2 - (c-a), \text{ s.t. } \ e \geq \max\left\{\sqrt{\frac{a}{k}}, \sqrt{\frac{c-a}{2k}}\right\}. \tag{D.1}$$

By considering the first order condition and the constraints, the optimal probability of delivery $e^* = \max\{\frac{v}{4k}, \sqrt{\frac{a}{k}}, \sqrt{\frac{c-a}{2k}}\}$. Depending on (c, a), we have the following three scenarios.

1. When $a < c - \frac{v^2}{8k}$, $\Pi_M < 0$ even at the unconstrained optima $\frac{v}{4k}$. Therefore, the manufacturer does not source from the supplier.
2. When $a \geq \max\left(c - \frac{v^2}{8k}, \frac{v^2}{16k}\right)$, we have $\sqrt{\frac{a}{k}} \geq \frac{v}{4k} \geq \sqrt{\frac{c-a}{2k}}$, and hence $e^* = \sqrt{\frac{a}{k}}$. Correspondingly, $\Pi_M = v\sqrt{\frac{a}{k}} - c - a > 0$ and $\Pi_s = 0$.
3. When $a \in \left[c - \frac{v^2}{8k}, \frac{v^2}{16k}\right)$, we have $\frac{v}{4k} \geq \sqrt{\frac{a}{k}} \geq \sqrt{\frac{c-a}{2k}}$, and hence $e^* = \frac{v}{4k}$. Correspondingly, $\Pi_M = \frac{v^2}{8k} - (c-a) > 0$ and $\Pi_s = \frac{v^2}{16k} - a \geq 0$.

For the last two scenarios, p and i_B follow directly from $p^* = 2ke^* + \frac{c-a}{e^*}$ and (3.3). □

Proposition D.0.1. *Under POF, charging the supplier a penalty upon failed delivery does not improve the performance of POF.*

Proof. Proof of Proposition D.0.1.

Due to limited liability, the supplier faces the same problem with a penalty: that he will lose his liquid assets a if he fails to deliver. Therefore, his acceptance constraint remains $e \geq \sqrt{\frac{a}{k}}$.

For the bank, its break-even constraint becomes $e(1+i_B)c + (1-e)(a+p_n) = c$, and thus its lending constraint becomes $e \geq \sqrt{\frac{c-a-p_n}{2k}}$. For the manufacturer, we can similarly substitute p in terms of e and plug it into the manufacturer's payoff. Her payoff stays the same as $\Pi_M = \min_{e,p_n}\{(1-e)v + 2ke^2 + (c-a)\}$, because the penalty is internalized by the bank's interest rate change. Therefore the optimal effort is $e^* = \max\{\frac{v}{4k}, \sqrt{\frac{a}{k}}, \sqrt{\frac{c-a-p_n}{2k}}\}$. The best the manufacturer can do is to make sure the bank's lending constraint is never binding by having $\max\{\frac{v}{4k}, \sqrt{\frac{a}{k}}\} \geq \sqrt{\frac{c-a-p_n}{2k}}$. Hence, the manufacturer can pick any $p_n \geq \max\left\{c - a - \frac{v^2}{8k}, c - 3a\right\}$ and Proposition 3.3.1 still holds. □

Proof. Proof of Corollary 3.3.1. This corollary follows directly from Proposition 3.3.1. First, it is easy to verify that the desired monotonicity holds for each of the three regions in Proposition 3.3.1. For example, when $a > \max\{c - \frac{v^2}{8k}, \frac{v^2}{16k}\}$, $p^* = 2\sqrt{ka} + \frac{k(c-a)}{\sqrt{ka}}$, $i_B = \left(\sqrt{\frac{k}{a}} - 1\right)\left(\frac{c-a}{c}\right)$, $e^* = \sqrt{\frac{a}{k}}$, $\Pi_M = v\sqrt{\frac{a}{k}} - c - a$, and $\Pi_S = 0$. Thus, we have $\frac{\partial p^*}{\partial k} > 0$, $\frac{\partial i_B}{\partial k} > 0$, $\frac{\partial e^*}{\partial k} < 0$, $\frac{\partial \Pi_S}{\partial k} = 0$, and $\frac{\partial \Pi_M}{\partial k} < 0$. Similar results hold when $a \in \left[c - \frac{v^2}{8k}, \frac{v^2}{16k}\right]$. For $a < c - \frac{v^2}{8k}$, all quantities are constant. Without loss of generality, we set $i_B^* = +\infty$, $e^* = 0$, and $p^* = v$.

Second, noting that all the above quantities are continuous and the derivatives have the same sign on the boundary between Regions I and II in Figure 3.2, the results hold. For the boundaries between Regions I and III and between Regions II and III, we can check the results also hold as $i_B^* = +\infty$, $e^* = 0$, $p^* = v$, $\Pi_M = 0$, and $\Pi_S = 0$ in Region III. □

Proof. Proof of Proposition 3.4.1. In BDF, the supplier's best response is given in (3.1), with i_B being replaced by i_M. By using the same approach as presented in the proof of Proposition 1, we can express p as a function of e, i.e. $p = 2k \cdot e + (1 + i_M)c - a$. Substituting this into the manufacturer's total payoff, we have $\Pi_M = -2ke^2 + ve - (c - a)$. As i_M does not appear in Π_M, the manufacturer can select any interest rate i_M satisfying $p = 2ke + (1 + i_M)c - a$. Consequently, the manufacturer's problem under the BDF scheme is $\Pi_M = \max_e \{-2ke^2 + ve - (c - a)\}$, subject to the supplier's participation constraint $e \geq \sqrt{\frac{a}{k}}$.

By considering the first order condition, the supplier's optimal effort is $e^* = \max\{\frac{v}{4k}, \sqrt{\frac{a}{k}}\}$. Similarly to the proof for Proposition 3.3.1, depending on (c, a), we have the following three scenarios.

1. When $a < c - \frac{v^2}{8k}$, $\Pi_M < 0$, the manufacturer does not source from the supplier.
2. When $a \geq \max\left(c - \frac{v^2}{8k}, \frac{v^2}{16k}\right)$, we have $e^* = \sqrt{\frac{a}{k}}$. Correspondingly, $\Pi_M = v\sqrt{\frac{a}{k}} - c - a$ and $\Pi_S = ke^2 - a = 0$. The manufacturer offers (p^*, i_M^*) such that $p^* - (1 + i_M^*)c = 2\sqrt{ak} - a$.
3. When $a \in \left[c - \frac{v^2}{8k}, \frac{v^2}{16k}\right)$, we have $e^* = \frac{v}{4k}$. Correspondingly, $\Pi_M = e(v - p) = \frac{v^2}{8k} - (c - a)$, $\Pi_S = \frac{v^2}{16k} - a$. The manufacturer offers (p^*, i_M^*) such that $p^* - (1 + i_M^*)c = \frac{v}{2} - a$.

$\square$

Proof. Proof of Lemma 3.2. Suppose not, that is, when the supplier is inefficient ($\tau = L$), the manufacturer chooses price p different from p_L^S in Proposition 3.3.1. By doing so, the manufacturer's payoff $\Pi_M(L, p, L)$ is strictly smaller than that in the symmetric information case ($\Pi_M(L, p_L^S, L)$). This contradicts the supposition. Therefore, the manufacturer would offer an inefficient supplier contract price p_L^S, the same as in Proposition 3.3.1. $\square$

Proof. Proof of Proposition 3.5.1.

First, consider the scenario where $a \geq \frac{v^2}{16k_H}$. We construct the bank's posterior belief as follows: When $p = p_H^S = 2\sqrt{k_H a} + \frac{k_H(c-a)}{\sqrt{k_H a}}$, the bank believes the supplier is efficient; otherwise, the bank believes that the supplier is inefficient. Under such a belief, observing $p = p_H^S$, the bank offers $i_{B,H} = \left(\sqrt{\frac{k_H}{a}} - 1\right)\left(\frac{c-a}{c}\right)$. If the manufacturer offers p_H^S to the inefficient supplier, facing p_H^S and $i_{B,H}$, according to (3.7), the inefficient supplier should choose $e_L^* = 0$ as $p_H^S < (1+i_{B,H})c+2\sqrt{k_L a}-a$, that is, p_H^S is unacceptable to him. Therefore, $\Pi_M(L, p_H^S, H) = 0 < \Pi_M(L, p_L^S, L)$ and hence the posterior belief above is rational. It is obvious that p_H^S is optimal for the efficient supplier under this belief; therefore, offering p_H^S corresponds to a separating PBE. Similarly, we can show that p_H^S also corresponds to a separating PBE when $a \in \left[\frac{v^2}{16k_L}, \frac{v^2}{16k_H}\right)$. Furthermore, it is obvious that the separating PBE above is the least costly as p_H^S is optimal under the symmetric information case. Combining the two scenarios leads to the first case of Proposition 3.5.1.

For the second case, i.e. $a < \frac{v^2}{16k_L}$ and $c - a \in \left(\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}, \frac{2k_L a}{k_H}\right)$, we prove our results in two steps. First, we show that $p_H = p_{L,H}^{SA} - \epsilon$ corresponds to a PBE. Then, we show that there is no separating PBE that is less costly. To show that $p_H = p_{L,H}^{SA} - \epsilon$ corresponds to a PBE, we construct the bank's posterior belief as follows: The bank believes the supplier is efficient when $p_H = p_{L,H}^{SA} - \epsilon$ and inefficient otherwise. Under such a belief, similar to the previous case, as p_H is unacceptable to the inefficient supplier, (3.10) holds, i.e. the above belief is rational. It is also easy to check that (3.11) also holds in this region, and hence, the manufacturer's action is optimal under this belief. Therefore, $p_{L,H}^{SA} - \epsilon$ corresponds to a PBE. To show that there is no separating PBE that is less costly, note that there exists no p_H that satisfy $\Pi_M(H, p_H, H) > \Pi_M(H, p_{L,H}^{SA} - \epsilon, H)$ and $\Pi_M(L, p_H, H) \leq \Pi_M(L, p_L^S, H)$ jointly; therefore, $p_{L,H}^{SA} - \epsilon$ is the most efficient separating equilibrium.

For the third case, i.e. $c - a \in \left[0, \min\{\frac{v^2}{8k_L}, \frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}\}\right] \cup \left[\frac{2k_L a}{k_H}, \frac{v^2}{8k_L}\right]$, the proof that p^{MI} corresponds to the least-costly separating equilibrium is similar to the second case and the details are omitted here.

Finally, for $c-a > \max\left\{\frac{v^2}{8k_L}, \frac{2k_La}{k_H}\right\}$, to show that no separating equilibrium exists, note that $\Pi_M(L, p_L^S, L) = 0$, and therefore, for (3.10) to hold, p_H must also satisfy that $\Pi_M(L, p_H, H) = 0$, i.e. $p_H \leq p_H^{BL}$. However, such p_H is not acceptable to the efficient supplier. Therefore, there exists no p_H which the supplier would be willing to bring to the bank for POF while the bank believes the supplier is efficient. □

Proof. Proof of Proposition 3.5.2. When $c-a \leq \frac{v^2}{8k_W}$, we construct the bank's posterior belief as follows: If the bank observes $p = p_W^* = \frac{v}{2} + \frac{4k_W(c-a)}{v}$, then the bank's belief remains the same as its prior. Otherwise, the bank believes the supplier is inefficient. Under such a belief, observing $p = p_W^*$, the bank offers $i_{B,W}$ according to (3.12), which leads to the supplier's optimal effort $e_\tau = \frac{v}{4k_\tau}$ and $\Pi_M(\tau, p_W^*, W) = \frac{v^2}{8k_\tau} - \frac{4k_W(c-a)}{k_\tau}$ for $\tau = \{H,\ L\}$. It is easy to show that $\Pi_M(\tau, p_W^*, W) > \max_{p \neq p_W^*} \Pi_M(\tau, p, L)$ for both $\tau \in \{H, L\}$. Hence p_W^* and the above belief corresponds to a pooling PBE. To show that it corresponds to the Pareto-dominating one, we note that $p_W^* = \arg\max_p \Pi_M(\tau, p, W)$ for $\tau \in \{H, L\}$.

Finally, when $c-a > \frac{v^2}{8k_W}$, it is easy to check that the bank is not willing to lend under any pooling equilibrium because $p_W > v$. Hence, no pooling equilibrium exists. □

Proof. Proof of Proposition 3.5.3.

It is obvious that in our setting the Intuitive Criterion eliminates all separating PBE except for the least costly one and eliminates all pooling equilibria except for the Pareto-dominating one. The details are omitted here. Furthermore, for $c-a \in \left[\max\{\frac{2k_La}{k_H}, \frac{v^2}{8k_L}\}, \frac{v^2}{8k_W}\right]$, no separating equilibrium exists. Hence, it is easy to show that the Pareto-dominating pooling equilibrium survives the Intuitive Criterion. Similarly, for $c-a \in \left(\frac{v^2}{8k_L},\ \frac{2k_La}{k_H}\right)$, the least-costly separating equilibrium survives the Intuitive Criterion.

For $c-a \in \left(0,\ \left(1 + \frac{\lambda k_L}{(1-\lambda)k_H}\right)\frac{(v-4\sqrt{k_La})^2}{8(k_L-k_H)}\right) \cup \left(\frac{2k_La}{k_H},\ \frac{v^2}{8k_L}\right)$, in the Pareto-dominating pooling equilibrium, $\Pi_M(\tau, p_W^*, W) = \frac{v^2}{8k_\tau} - \frac{k_W(c-a)}{k_\tau}$ for $\tau = H,\ L$. It is clear that $\Pi_M(L, p_W^*, W) > \Pi_M(L, p_L^S, L)$, i.e. the manufacturer facing an inefficient supplier is better off under the pooling equilibrium. When the manufacturer faces the efficient supplier, for $c-a \in \left(0, \frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}\right] \cup \left(\frac{2k_L a}{k_H}, \frac{v^2}{8k_L}\right)$, in the least-costly separating equilibrium, $\Pi_M(H, p^{MI}, H) = \frac{v^2}{8k_H} - \frac{k_L}{k_H}(c-a)$, which is less than $\Pi_M(H, p_W^*, W)$. Similarly, for $c-a \in \left(\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}, \ \min\left\{\frac{v^2}{8k_L}, \frac{2k_L a}{k_H}, \left(1+\frac{\lambda k_L}{(1-\lambda)k_H}\right)\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}\right\}\right)$, in the least-costly separating equilibrium, $\Pi_M(H, p_{L,H}^{SA}, H) = v\sqrt{\frac{k_L a}{k_L}} - \frac{2k_L a}{k_H} - (c-a)$, which is also less than $\Pi_M(H, p_W^*, W)$. Therefore, in this region the manufacturer is better off in the above pooling equilibrium than in the least-costly separating one, regardless of the supplier's type.

Finally, for $c-a \in \left[\left(1+\frac{\lambda k_L}{(1-\lambda)k_H}\right)\frac{(v-4\sqrt{k_L a})^2}{8(k_L-k_H)}, \ \min\{\frac{2k_L a}{k_H}, \frac{v^2}{8k_W}\}\right]$, in the Pareto-dominating pooling equilibrium, assume the manufacturer facing an efficient supplier deviates to $p_H = p_{L,H}^{SA} - \epsilon$. Under this price, $\Pi_M(L, p_{L,H}^{SA} - \epsilon, H) < \Pi_M(L, p_W^*, W)$; therefore, under any reasonable belief, the bank should reclassify the supplier as efficient when it observes $p_{L,H}^{SA} - \epsilon$. Under this belief, $\Pi_M(H, p_{L,H}^{SA} - \epsilon, H) > \Pi_M(H, p_W^*, W)$. Therefore, deviating to $p_{L,H}^{SA} - \epsilon$ is profitable for the efficient supplier; hence, the Intuitive Criterion eliminates the pooling equilibrium as desired. □

Proof. Proof of Corollary 3.5.1. Note that for $a < \frac{v^2}{16k_L}$, under symmetric information, the manufacturer's payoff facing an efficient supplier is $\Pi_M = \frac{v^2}{8k_H} - (c-a)$.

In Region SA^* of Proposition 3.5.3, $\Pi_M(H, p_{L,H}^{SA}, H) = \frac{v\sqrt{k_L a}}{k_H} - \frac{2k_L}{k_H}a - (c-a)$. Therefore, $\Delta_M = \frac{(v-4\sqrt{k_L a})^2}{8k_H}$. Taking partial derivatives of Δ_M with respect to a, v, λ and k_H, we have $\frac{\partial \Delta_M}{\partial a} = -\frac{(v-4\sqrt{ak_L})}{2k_H}\sqrt{\frac{k_L}{a}} < 0$, $\frac{\partial \Delta_M}{\partial v} = \frac{v-4\sqrt{ak_L}}{4k_H} > 0$, $\frac{\partial \Delta_M}{\partial \lambda} = 0$, and $\frac{\partial \Delta_M}{\partial k_H} = -\frac{(v-4\sqrt{ak_L})^2}{8k_H^2} < 0$.

In Region P, $\Pi_M(H, p_W^*, W) = \frac{v^2}{8k_H} - \frac{k_W}{k_H}(c-a)$, $\Delta_M = \left(\frac{k_W}{k_H} - 1\right)(c-a) = \frac{\frac{k_L}{k_H} - 1}{1+\frac{\lambda}{1-\lambda}\frac{k_L}{k_H}}(c-a)$. Similarly, $\frac{\partial \Delta_M}{\partial a} = -\frac{(1-\lambda)(k_L-k_H)}{\lambda k_L + (1-\lambda)k_H} < 0$, $\frac{\partial \Delta_M}{\partial v} = 0$, $\frac{\partial \Delta_M}{\partial \lambda} = -\frac{k_L(k_L-k_H)}{(\lambda k_L+(1-\lambda)k_H)^2}(c-a) < 0$, and $\frac{\partial \Delta_M}{\partial k_H} = -\frac{(1-\lambda)k_L}{(\lambda k_L+(1-\lambda)k_H)^2}(c-a) < 0$. □

REFERENCES

Acemoglu, D., V.M. Carvalho, A. Ozdaglar, A. Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *The Journal of Finance* **80**(5) 1977–2016.

Acemoglu, D., A. Ozdaglar, A. Tahbaz-Salehi. 2015a. Networks, shocks, and systemic risk. *The Oxford Handbook on the Economics of Networks* .

Acemoglu, D., A. Ozdaglar, A. Tahbaz-Salehi. 2015b. Systemic risk and stability in financial networks. *American Economic Review* **105**(2) 564–608.

Ahern, K.R. 2013. Network centrality and the cross section of stock returns Working Paper, Marshall School of Business, University of Southern California.

Ang, E, D.A. Iancu, R. Swinney. 2015. Disruption risk and optimal sourcing in multi-tier supply networks. *Management Science* Forthcoming.

Anupindi, R., R. Akella. 1993. Diversification under supply uncertainty. *Management Sciences* **39**(8).

Atalay, E., A. Hortaçsu, J. Roberts, C. Syverson. 2011. Network structure of production. *Proceedings of National Academy of Science* **108**(13).

Atalay, E., A. Hortasu, C. Syverson. 2014. Vertical integration and input flows. *American Economic Review* **104**(4).

Aydin, G., V. Babich, D. Beil, Z. Yang. 2011. Decentralized supply risk management. *The Handbook of Integrated Risk Management in Global Supply Chains* 387–424.

Babich, V. 2010. Independence of capacity ordering and financial subsidies to risky suppliers. *Manufacturing & Service Operations Management* **12**(4) 583–607.

Babich, Volodymyr, Christopher S Tang. 2012. Managing opportunistic supplier product adulteration: Deferred payments, inspection, and combined mechanisms. *Manufacturing & Service Operations Management* **14**(2) 301–314.

Badrinath, S., J. Kale, T. Noe. 1995. Of shepherds, sheep, and the cross-autocorrelations in equity returns. *Review of Financial Studies* **8**.

Balch, T. 2013. Assessment of a supply chain-based indicator for stock trading URL `http://augmentedtrader.com/2013/07/26/assessment-of-a-supply-chain-based-indicator-for-stock-trading/`.

Banz, R.W. 1981. The relationship between return and market value of common stocks. *Journal of Finance* **9**(1).

Barberis, N., A. Shleifer, R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* **49**(3).

Berk, J.B., R.C. Green, V. Naik. 1999. Optimal investment, growth options, and security returns. *Journal of Finance* **54**(5).

Biais, B., C. Gollier. 1997. Trade credit and credit rationing. *Review of Financial Studies* **10**(4) 903–937.

Bimpikis, Kostas, Ozan Candogan, Shayan Ehsani. 2015. Supply disruptions and optimal network structures. Tech. rep., Working Paper.

Boesler, M. 2013. A trading strategy involving apple suppliers has apparently been way more profitable than investing in apple itself. *Yahoo Finance* URL `http://finance.yahoo.com/news/trading-strategy-involving-apple-suppliers-180543300.html`.

Bonacich, P. 1972. Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology* **2**.

Bonacich, P., P. Lloyd. 2001. Eigenvector-like measures of centrality for asymmetric relations. *Social Networks* **22**(3).

Bondt, W.F.M., R. Thaler. 1985. Does the stock market overreact. *Journal of Finance* **40**(3).

Borgatti, S.P. 2005. Centrality and network flow. *Social Networks* **27**.

Brennan, M., N. Jegadeesh, B. Swaminathan. 1993. Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies* **6**.

Buzacott, J.A., R.Q. Zhang. 2004. Inventory management with asset-based financing. *Management Science* **50**(9) 1274–1292.

Cachon, Gérard P, Martin A Lariviere. 2001. Contracting to assure supply: How to share demand forecasts in a supply chain. *Management science* **47**(5) 629–646.

Cachon, G.P., T. Randall, G.M. Schmidt. 2007. In search of the bullwhip effect. *Manufacturing Service Oper. Management* **9**(4).

Cahan, R., Z. Chen, S. Wang, Y. Luo, M. Alvarez, J. Jussa. 2013. Signal processing: uncovering hidden economic links Deutsche Bank Markets Research,March 28, 2013.

Candogan, Ozan, Kostas Bimpikis, Asu Ozdaglar. 2012. Optimal pricing in networks with externalities. *Operations Research* **60**(4).

Carhart, M.M. 1997. On persistence in mutual fund performance. *Journal of Finance* **52**(1).

Carvalho, V.M., X. Gabaix. 2013. The great diversification and its undoing. *American Economic Review* **103**(5).

Chen, Yibin, Diwakar Gupta. 2014. Trade-finance contracts for small-business suppliers and the effect of third-party financing. *Available at SSRN 2486757* .

Cheng, P. 2015. Personal Communication. Chairman of Hanbo Enterprise.

Cho, In-Koo, David M Kreps. 1987. Signaling games and stable equilibria. *The Quarterly Journal of Economics* 179–221.

Chordia, T., B. Swaminathan. 2000. Trading volume and cross-autocorrelations in stock returns. *Journal of Finance* **52**.

Clauset, A., C.R. Shalizi, M.E.J. Newman. 2009. Power-law distribution in empirical data. *SIAM Review* **51**.

Cohen, L., A. Frazzini. 2008. Economic links and predictable returns. *Journal of Finance* **63**(4).

Dong, L., S. Y. Tang, B. Tomlin. 2015. Production chain disruptions: Inventory, preparedness, and insurance. Working Paper.

Dong, Lingxiu, Brian Tomlin. 2012. Managing disruption risk: The interplay between operations and insurance. *Management Science* **58**(10) 1898–1915.

Elliott, Matthew, Jonathon Hazell. 2015. Endogenous financial networks: Efficient modularity and why shareholders prevent it Working paper.

Fama, E.F., K.R. French. 1988. Permanent and temporary components of stock prices. *Journal of Political Economy* **96**(2).

Fama, E.F., K.R. French. 1993. Common risk factors in the returns on bonds and stocks. *Journal of Financial Economics* **33**(1).

Fama, E.F., J.D. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* **81**(3).

Fruchterman, T., E. Reingold. 1991. Graph drawing by force-directed placement. *Journal of Software: Practice and Experience* **21**(11).

Fruin, P., J. Osiol, K. Wang. 2012. Supply chain interactions part 1: industries S&P Capital IQ Research.

Fung, Victor K, William K Fung, Yoram Jerry R Wind. 2007. *Competing in a flat world: building enterprises for a borderless world*. Pearson Prentice Hall.

Gustin, D. 2014. Purchase order finance, the tough nut to crack. URL `http://spendmatters.com/tfmatters/purchase-order-finance-the-tough-nut-to-crack/`. Accessed at August 20, 2015.

Hendricks, K.B., V.R. Singhal. 2003. The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management* **21**(5).

Hou, K. 2006. Industry information diffusion and the lead-lag effect in stock returns. *Review of Financial Studies* **20**.

Hou, K., T. Moskowitz. 2005. Market frictions, price delay, and the cross-section of expected returns. *Review of Financial Studies* **18**.

Hou, K., D. Robinson. 2006. Industry concentration and average stock returns. *Journal of Finance* **71**(4).

Hwang, W., N. Bakshi, V. DeMiguel. 2014. Simple contracts for reliable supply: Capacity versus yield uncertainty. *London Business School, Working paper* .

Jackson, Matthew, Asher Wolinsky. 1996. A Strategic Model of Social and Economic Networks. *Journal of Economic Theory* **71** 44–74.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance* **45**(3).

Jegadeesh, N., S. Titman. 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* **48**(1).

Johnson, T. 2002. Rational momentum effects. *Journal of Finance* **57**(2).

Jorion, P., G. Zhang. 2009. Credit contagion from counterparty risk. *Journal of Finance* **64**(5).

Kelly, B., H.N. Lustig, S.V. Nieuwerburgh. 2013. Firm volatility in granular networks Working paper, Booth School of Business, University of Chicago.

Klapper, L. 2006. The role of factoring for financing small and medium enterprises. *Journal of Banking and Finance* **30**(11) 3111–3130.

Kouvelis, P, L. Dong, O. Boyabatli, R. Li. 2011. *Handbook of integrated risk management in global supply chains*, vol. 1. John Wiley & Sons.

Kouvelis, P., W. Zhao. 2012. Financing the newsvendor: supplier vs. bank, and the structure of optimal trade credit contracts. *Operations Research* **60**(3) 566–580.

Laffont, J., D. Martimort. 2009. *The theory of incentives: the principal-agent model*. Princeton university press.

Lai, G., W. Xiao. 2014. Signals to partially informed investors: Inventory distortion and realization of stock-based payment. *Available at SSRN* .

Lai, Guoming, Laurens Debo, Lin Nan. 2011. Channel stuffing with short-term interest in market value. *Management Science* **57**(2) 332–346.

Latour, A. 2001. A fire in albuquerque sparks crisis for european cell-phone giants. *Wall Street Journal* .

Li, Cuihong. 2013. Sourcing for supplier effort and competition: Design of the supply base and pricing mechanism. *Management Science* **59**(6) 1389–1406.

Lintner, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics* **47**(1).

Lo, A.W., A.C. MacKinlay. 1990. When are contrarian profits due to stock market overreaction? *Review of Financial Studies* **3**.

Lucas, Jr, R.E. 1977. Understanding business cycles. *Kiei Conference on Growth without Inflation* .

Martin, Andrew. 2010. The places they go when banks say no. *New York Times* .

Menzly, L., O. Ozbas. 2010. Market segmentation and cross-predictability of returns. *Journal of Finance* **65**(4).

Moskowitz, T.J., M. Grinblatt. 1999. Do industries explain momentum? *Journal of Finance* **54**.

Osadchiy, N., V. Gaur, S. Seshadri. 2015. Systematic risk and the bullwhip effect in supply chains Emory University Goizueta Business School, working paper.

Pástor, L., R.F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* **111**.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* **22**.

Petersen, M.A., R.G. Rajan. 1997. Trade credit: theories and evidence. *Review of Financial Studies* **10**(3) 661–691.

Porteus, E. L. 1985. Investing in reduced setups in the eoq model. *Management Science* **31**(8) 998–1010.

Riley, John G. 2001. Silver signals: Twenty-five years of screening and signaling. *Journal of Economic Literature* **39**(2) 432–478.

Rosernberg, B., K. Reid, R. Lanstein. 1985. Persuasive evidence of market inefficiency. *Journal of Portfolio Management* **11**(3).

Rui, H., G. Lai. 2015. Sourcing with deferred payment and inspection under supplier product adulteration risk. *Production and Operations Management* .

Sagi, J.S., M.S. Seasholes. 2007. Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics* **84**(2).

Salvini, M., S. Mesomeris, J.R. Avettand-Fenoel, Y. Wang. 2012. Quantitative musing: sales segment momentum Deutsche Bank Quantitative Strategy.

Schmidt, W., V. Gaur, R. Lai, A. Raman. 2015. Signaling to partially informed investors in the newsvendor model. *Production and Operations Management* **25**(3) 383–401.

Shahrur, H., Y. Becker, D. Rosenfeld. 2010. Return predictability along the supply chain: the international evidence. *Financial Analysis* **66**(3).

Sharpe, W.F. 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance* **19**(3).

Sodhi, M., C.S. Tang. 2012. *Managing Supply Chain Risks*. Springer, New York.

Spence, Michael. 2002. Signaling in retrospect and the informational structure of markets. *American Economic Review* 434–459.

Swinney, R., S. Netessine. 2009. Long-term contracts under the threat of supplier default. *Manufacturing & Service Operations Management* **11**(1) 109–127.

Tang, C. S. 2006. Perspectives in supply chain risk management. *International Journal of Production Economics* **103**(2) 451–488.

Tang, S. Y, H. Gurnani, D. Gupta. 2014. Managing disruptions in decentralized supply chains with endogenous supply process reliability. *Production and Operations Management* **23**(7) 1198–1211.

Tice, C. 2010. Can a Purchase Order Loan Keep Your Business Growing? URL `http://www.entrepreneur.com/article/207058`. Accessed at March 10, 2015.

Tomlin, B., Y. Wang. 2011. Operational strategies for managing supply chain disruption risk. P. Kouvelis, O Boyabatli, L. Dong, , R Li, eds., *The Handbook of Integrated Risk Management in Global Supply Chains*. Wiley Online Library, 79–101.

Tunca, T.I., W. Zhu. 2014. Buyer Intermediation in Supplier Finance. University of Maryland working paper.

Watkins, Simon. 2012. Top uk firms lend billions to struggling suppliers as they are forced to act as banks URL `http://www.dailymail.co.uk/money/news/article-2220517/Top-UK-firms-lend-billions-suppliers-forced-act-banks.html`.

Yang, S. A., J. R. Birge. 2009. How Inventory is (Should Be) Financed: Trade Credit in Supply Chains with Demand Uncertainty and Costs of Financial Distress. *SSRN eLibrary* doi:10.2139/ssrn.1734682.