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Risky Suppliers or Risky Supply Chains? An Empirical Analysis of Sub-tier Supply Network Structure on Firm Performance in the High-Tech Sector

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Past research in supply chain risk management has focused on the interactions between buyers and their immediate suppliers and/or assumed independence of risks imposed by these suppliers. However, supply network structure may induce inter-dependency of risks due, for example, to overlapping sub-tier suppliers. This paper empirically studies the prevalence of overlapping sub-tier suppliers and their impact on financial performance for firms in the high-tech sector. Using firm-level supplier-customer relationship data, we find that on average 20 (2.3) percent of tier-2 suppliers are shared by at least two (five) tier-1 suppliers. We also find that the risk, measured as stock return volatility, of the focal tier-0 firm is positively associated with common tier-2 supplier risk, and the association is stronger for suppliers with a higher degree of tier-2 commonality. To disentangle the impact of risky supply network structure from risky tier-2 suppliers, we define two network metrics, viz., *diamond ratio* and *cosine commonality score*. We find that a one standard deviation increase in each of these metric leads to an increase in standard deviation of 0.58 and 0.41 respectively in tier-0 firm's risk. Our results reveal substantial unmanaged supply chain risks due to overlapping sub-tier suppliers, and highlight the need for firms to increase visibility into their extended supply network.

1. Introduction

In the past decade firms have encountered an ever-increasing number of supply chain disruptions, triggered by a wide range of natural and man-made causes such as earthquake, flood, fire, labor protest, financial crisis and political unrest. These events have led to substantial short-term (production delay, increased labor and supply costs) and long-term (market share erosion, bankruptcy) losses.

As a consequence, supply chain risk management has become an active area of research. One stream of research analyzes the role of inventory in protecting firms against supply chain disruptions (see Parlar and Berkin 1991, Parlar 1997, Qi et al. 2009, for example). Others explore the use of supplier diversification as a viable strategy to mitigate supply chain risks (see Li et al. 2010, Babich et al. 2007, for example). Additionally, scholars have also looked into the benefit of flexibility (Tang and Tomlin 2008, Huchzermeier and Cohen 1996), vertical integration (Braunscheidel and Suresh 2009) and the level of trust between supply chain partners (Bode et al. 2011) on firms' supply chain agility. Sodhi and Chopra (2004) broadly categorize seven types of supply chain risks and discuss the drivers of each risk category and their mitigation strategies. The majority of this literature, however, focuses on the risk management of immediate suppliers. Only recently have scholars begun to investigate the role of sub-tier supply network structure on firms' risk mitigation strategies (Ang et al. 2015, Bakshi and Mohan 2015). The Japan tsunami and the Thailand flood of 2011, considered watershed events, brought into sharp focus opaqueness of the sub-tier structure and a firm's exposure to it. In fact such information black holes turned out to be a firm's Achilles heel (Brennan 2011):

> *The shortages of components from our tier one suppliers were bad news. Still, the real nail biter was the possibility that a raw material* ***deep in the supply chain*** *could be unavailable. A raw material outage can affect hundreds of supplier parts and thousands of our products. It was nerve wracking having to wait weeks for news to percolate up from the* ***sub-tiers*** *where we had so* ***little visibility****.*

Based on responses from 525 firms in 71 countries spanning 14 different industries, the 2014 Supply Chain Resilience Survey reveals that 51 percent of supply chain disruptions originate from two or more tiers deep in the supply chain (Business Continuity Institute 2014). The same report also finds that 13 percent of organizations are unaware of where a disruption originates. The LexisNexis Group (2013) corroborates this finding, suggesting that almost 40 percent of reported supply chain disruptions originate from tier-2 and tier-3 suppliers. These findings underscore the importance of the need to develop sub-tier visibility for a company's supply chain risk management agenda. Indeed, Toyota, Cisco, and P&G have initiated significant efforts to identify their sub-tier suppliers (Sáenz and Revilla 2013). Putting together such a map, usually with the help of their tier-1 suppliers, however, is not always an easy undertaking because manufacturers rarely have direct relationships with their sub-tier suppliers. In fact several manufactures, for example, Toyota, Boeing and Migros, have reported that their tier-1 suppliers are reluctant or unwilling to disclose full details regarding their suppliers (Grimm 2013).

Not only is it important to know who the sub-tier suppliers are, the structure of the network that binds them together could also be important. For example, when many tier-1 suppliers share a common tier-2 supplier, the supply base has a single-point of failure. But the structure of the sub-tier supply base appears to be even more of a mystery to many. "*We thought our supply chain was pyramid shaped, but it turned out to be barrel-shaped,*" said a Toyota Motor Corporation spokesman in a Japan Times article (Brennan 2011).

Uncovering the structure of sub-tier supply chain will be quite effort intensive and worthwhile only when there are significant benefits for such an undertaking. Our paper represents the first empirical attempt to study the nature and impact of sub-tier supply network structure on firm performance. One of the major challenges to study sub-tier suppliers is the lack of relevant data. Previous empirical studies in supply chain management typically use the *sector-level* US input-output table of material flows (e.g., Cachon et al. 2007, Osadchiy et al. 2015). The most commonly used *firm-level* supply-customer relationship data source, Compustat, only identifies the immediate customers who contribute more than 10% of revenues to the focal firm. This dataset cannot reliably identify suppliers, because major suppliers of small to medium customer firms and international suppliers are under-represented in the dataset. The recent availability of more complete firm-level supplier-customer data has enabled supply chain studies at a more granular level. For example, Jain et al. (2013) use transaction-level Import/Export data to build a one-step relationship between US and overseas firms. Bellamy et al. (2014) use Connexiti's supply chain database to examine the impact of supply network accessibility on firm's innovation output.

Over the past decade firms have increasingly relied on global suppliers to take advantage of lower input costs and geographical skill specialization (Hausman et al. 2005). Because Compustat data largely focuses on domestic relationships, it is not an ideal platform to study global supply chain relationships. Neither is the US Import/Export data, which contains only one-step cross-border relationship. We therefore rely on a new data source, Bloomberg, whose new Supply Chain Function maps 35,000 firms with their suppliers and customers. This data is more comprehensive than Compustat and US Import/Export. For example, for S&P 500 high-tech firms, the total number of suppliers, international and domestic, identified by Bloomberg is on average seven times larger than that identified by Compustat.

Using Bloomberg data, but with a focus on domestic supply networks, Wu and Birge (2014) study the influence of immediate supplier returns on firm returns across all sectors. In contrast, using Bloomberg we collect both domestic and international supply chain relationships and characterize the structure of a multi-tier supply network for high-tech firms worldwide. We choose the high-tech sector as our test bed because it is among the top few sectors that reportedly face a higher frequency of supply chain disruptions, and the industry's hyper-competitive nature and rapid growth rate imply more severe financial impacts of such disruptions.

Our supply network contains 4,538 firms, including 2,646 high-tech firms, 1,890 non-high-tech suppliers, and 13,670 directional links. Using this dataset, we study the nature, structure, and influence of tier-2 supplier commonality on the performance of focal tier-0 firms. There are several reasons why we focus on tier-2 supplier commonality. First, it has been the recent focus of some of the world's largest manufacturers. For example, Toyota discovered that many of its tier-1 suppliers share some of, or even all of, their tier-2 suppliers (Masui and Nishi 2012). Resilinc (www.resilinc.com), a supply chain risk management company, also finds similar patterns in their clients' supply networks spanning multiple industries including high-tech, automotive and chemicals (Resilinc 2013).

Second, Tier-2 supplier commonality results in interdependent risk patterns among tier-1 suppliers, which presents new challenges to the effectiveness of traditional risk mitigation efforts that treat suppliers as isolated. For example, Ang et al. (2015) conclude that an overlap in the tier-2 supply base is a critical factor that influences a manufacturer's optimal risk mitigation strategy. Specifically, they find that when a greater overlap is observed, firms should increasingly rely on supply chain contracts to induce tier-1 suppliers to mitigate sourcing risks, as opposed to using direct mitigation strategies such as multi-sourcing or holding excess inventory.

From the perspective of a tier-0 firm, tier-2 supplier commonality gives rise to a network structure that takes the shape of a diamond (Japan METI 2011). To characterize the diamond shape in supply networks, we propose several metrics including degree of commonality (unweighted), diamond ratio (unweighted) and cosine commonality score (weighted by cost-of-goods-sold). Using these metrics, we document the prevalence of overlapping sub-tier suppliers in the high-tech sector. Specifically, we find that on average 20 percent of tier-2 suppliers are shared by two or more tier-1 suppliers and 2.3 percent of tier 2 suppliers are shared by at least five tier-1 suppliers. We then quantify the impact of the tier-2 supplier commonality on the risk of the tier-0 firm, which is measured as stock return volatility as in Hendricks and Singhal (2005b). First, we find a positive and significant association between *common* tier-2 supplier risk and tier-0 firm risk. This association increases with the degree of commonality, measured as the number of tier-1 suppliers who share a tier-2 supplier. In particular, when a tier-2 supplier is shared by five or more tier-1 suppliers, one standard deviation increase in tier-2 supplier risk is associated with 0.79 standard deviation increase in tier-0 firm risk. Second, we separate the impact of risks that originate from the supply network structure and of those that originate from the suppliers. Using the diamond ratio, an unweighted measure of tier-2 commonality, and cosine commonality score, a cost-of-goods-sold (COGS) weighted measure, we quantify the direct impact of the sub-tier network structure on a tier-0 firm's risk. We find that, one standard deviation increase in the diamond ratio (cosine commonality score) leads to 0.58 (0.41) standard deviation increase in a tier-0 firm's risk, while controlling for average tier-1 and tier-2 supplier risks, market risk, and various firm-specific financial and operational characteristics. Given that both tier-0 firms and tier-1 suppliers have very limited knowledge of sub-tier network structure and its impact, they are unlikely to take endogenous actions to hedge against such risk coming from shared tier-2s. Consequently, the effect of tier-2 commonality that we measure here is likely causal and immune to omitted variable biases.

In summary, our results reveal substantial unmanaged supply chain risks due to sub-tier overlaps and highlight the need for firms to increase visibility into their extended supply network. In particular, firms should identify critical sub-tier suppliers shared by multiple immediate suppliers and manage their risks effectively.

2. Literature Review and Hypotheses Development

Mostly due to lack of relevant supply chain data, empirical research in supply chain risk management has been sparse. Hendricks and Singhal (2003, 2005a,b) pioneered this line of research by using event studies to quantify the negative effect of supply chain disruptions on firm stock price. They measured change in financial performance using abnormal stock returns and return volatility around the date when a supply chain disruption was announced to the public. Subsequent studies extend this line of work to analyze how firm characteristics and actions mitigate the impact of disruption risks. Hendricks et al. (2009) find that greater operational slack and lower geographic diversification reduces the impact of disruptions. Schmidt and Raman (2015) find that actions to improve operational efficiency have different impacts on firms facing distinct types of disruptions. Note this line of research focuses on publicly announced supply chain disruptions, but not the source of the disruption, immediate tier vs. sub-tiers, or the embedded network structure that may facilitate or prevent the propagation of the original event.

In order to link disruptions originating from sub-tier suppliers to the performance of tier-0 firms, it will be ideal to be able to track supply chain disruptions and in particular, identify their origins. Collecting a sufficiently large number of supply chain risk events and identifying their nature and origins is clearly a daunting task and beyond the scope of this paper. Instead, using firm-level data, we link the financial performance, measured by stock return volatility (Hendricks and Singhal 2005b), of sub-tier suppliers and tier-0 firms. Prior work has established the association of firms' operational and financial performances both theoretically (Gaur and Seshadri 2005) and empirically (Gaur et al. 2005). Consequently, we would expect that the association of sub-tier suppliers and tier-0 firms introduced by supply chain relationships will be reflected in the association of their financial performances as well.

Lately, using the Compustat data researchers have analyzed one-step supplier-customer connectivity. Cohen and Frazzini (2008) find that stock returns of principal customer firms can forecast future returns of supplier firms. Serpa and Krishnan (2015) empirically test how firm productivity is affected by productivity of its customer base. Both papers focus on direct one-step supply chain relationships and the impact (or predictability) of customer performances on supplier performances. Extending this line of inquiry, the next set of logical questions to ask include: 1) does connectivity with sub-tier suppliers also matter for the tier-0 firm's performance? 2) If so, which sub-tier suppliers matter more? 3) In particular, does the sub-tier network structure matter?

On the one hand, several recent industry reports cited earlier identify that a large number of supply chain disruptions originate from suppliers below tier-1. Risks that originate from suppliers in the extended supply chain have also been characterized in recent theoretical developments in supply chain risk management. Christopher and Lee (2004) point out that increasing end-to-end visibility is critical in mitigating supply chain risks. Using simulation, Schmitt and Singh (2012) show that viewing the supply network as a whole can improve the resilience of a multi-echelon supply chain. In the economics literature, using network analysis of input-output flows, Acemoglu et al. (2012) provide a proof on how idiosyncratic shocks of individual firms or sectors can aggregate through the supply network to become systematic shocks. Acemoglu et al. (2015) observe consistent patterns in the propagation of sector-level shocks through input-output linkages. A clear inference from these two last papers is that sub-tier suppliers play a role in the risk aggregation towards tier-0 firms because idiosyncratic shocks propagate beyond immediate neighbors.

On the other hand, if intermediate tier-1 suppliers, through appropriate mitigating actions, have fully internalized the risks from the tier-2 suppliers, sub-tier supplier risks may not be an *additional* source of risk to the tier-0 firm. For example, Hopp and Yin (2006) show that it is sufficient to simply build excess inventory or excess capacity at tier-1 supplier to hedge against supplier risks. This conclusion, however, is only demonstrated for supply networks that take an arborescent structure, wherein tier-1 suppliers' sub-networks are isolated from each other. Thus, it is a priori not obvious whether or not sub-tier suppliers impact the financial performance of the tier-0 firm, which leads to our first hypothesis:

HYPOTHESIS 1. *The financial risk of a tier-0 firm is positively associated with the financial risks coming from its tier-2 suppliers, while controlling for average tier-1 suppliers' risks.*

Should connectivity with tier-2 suppliers matter for tier-0 firms' performance, a legitimate follow-up question is which tier-2 suppliers would matter more? If most supply networks are indeed "barrel-shaped" rather than "pyramid-shaped" as Toyota discovered post Japan earthquake and tsunami, such a "barrel-shaped" structure induced by overlapping tier-2 suppliers in multiple tier-1s' subnetworks will create risk interdependencies among the tier-1 suppliers. With interdependent risks, merely controlling for average tier-1 supplier risk will be insufficient. Yang et al. (2012) find that inter-dependence between supplier disruptions reduces buyers' diversification benefits. Masih-Tehrani et al. (2011) show that ignoring inter-dependency in supplier risks will lead to cost underestimation and overstock in a multi-source supply chain. It is worth noting that interdependencies of supplier risks can be introduced for multiple reasons, including geographical proximity, common macro-economic shocks and overlapping supplier base. We focus on analyzing the impact of interdependency caused by overlapping suppliers. Our conclusions are robust to the inclusion of measures of tier-1 supplier geographical concentration and sub-sector concentration to account for other sources of interdependencies, as shown in the Section 6.2.

Ang et al. (2015) explicitly model supply networks with and without overlapping tier-2 suppliers and compare the optimal risk mitigation strategy for a tier-0 firm. They conclude that the tier-0 firm's optimal risk mitigation strategy depends critically on the *degree* of tier-2 supplier overlap. When there is a higher degree of overlap, direct mitigation strategies (e.g., safety stock and multi-sourcing) are less effective than indirect strategies such as supply chain contracts, which induce tier-1 suppliers to mitigate the upstream risk. We therefore hypothesize that shared tier-2 suppliers matter more than non-shared tier-2 suppliers for tier-0 firms' risks. The association is stronger when the degree of overlapping is larger, i.e., shared by more tier-1 suppliers.

HYPOTHESIS 2. *The risk of a tier-0 firm is positively associated with the risks coming from its common tier-2 suppliers shared by more than one tier-1 supplier, and the association is stronger with a higher degree of commonality.*

If the association between tier-0 firm risk and tier-2 supplier risk is stronger for more heavily shared tier-2 suppliers, can we disentangle the impact of tier-2 suppliers and the impact of level of sharing in the supply network? In other words, can we tell whether a tier-0 firm's risk comes from connectivity with risky tier-2 suppliers, or from having a risky supply network structure that imbeds heavy sub-tier overlapping? To investigate this, we need measures of supply network structure.

The social network literature posits several measures of network structure that have been used to study risk propagation and its impacts. In particular, the most commonly used ones are degree centrality (Wu and Birge 2014) and eigenvalue centrality (Acemoglu et al. 2012, Ahern 2013, Wu and Birge 2014). These measures, however, do not capture the distinct attributes unique to supply networks where firms are naturally sorted into tiers. We propose new network metrics that capture supply networks' sub-tier supplier commonality and test their impact on form performance. We hypothesize that sub-tier supplier commonality has a direct impact on tier-0 firm risk:

HYPOTHESIS 3. *A higher level of tier-2 commonality in a firm's supply network leads to greater risks for the firm, controlling for average tier-1 and tier-2 supplier risks.*

It is also worth noting that by separating the impact of sub-tier network structure from that of sub-tier suppliers, we measure the causal impact of network structure on tier-0 firm risk. This is because, while a tier-0 firm may control which tier-1 firms to source from and what risk mitigation actions to take based on its knowledge of tier-1 suppliers' risks, it is usually unaware and often does not control the level of sub-tier sharing. Similarly, tier-1 suppliers are also not knowledgeable about the identity of other tier-1 suppliers and who they source from, and therefore, unaware of the level of tier-2 sharing as well. The sub-tier network structure is thus exogenous to the unobserved risk mitigation decisions made by both tier-0 and tier-1 firms, allowing us to measure the unbiased causal effect.

3. Data

We collected supplier-customer relationship data from a new data source, Bloomberg, whose new Supply Chain Function maps 35,000 firms with their suppliers and customers. We present reasons why we choose the high-tech sector for the study of supply chain risks. We then compare supplier coverage of Bloomberg and Compustat and discuss the potential coverage bias in our data.

3.1. Supplier-Customer Relationship Data

We obtain information regarding global high-tech firms and their suppliers from Bloomberg, a privately held financial software, data and media company. Bloomberg established its new database of supplier-customer relationships using multiple sources. One source, similar to Compustat, relies on the SEC requirement that all US listed firms disclose their customers who comprise greater than 10% of annual revenues. In this SEC dataset, however, international suppliers are underrepresented, and so are large suppliers of relatively small customers due to the 10% revenue cutoff. Bloomberg's database supplements the SEC dataset with information that firms disclose in a variety of media, such as annual and quarterly reports, conference call transcripts, capital markets presentations, sell-side conferences, company press releases, company websites, etc. (Davenport 2011). Using data gleaned from these sources documented in several languages, the Bloomberg database offers a comprehensive view of firm-level global supply chain relationships.

The Bloomberg dataset currently comprises supply chain relationships of 35,000 companies, and reports the source and date for each of these identified relationships. For each relationship, it also categorizes the nature of the product or service accounted for by the customer firm in the following four buckets: cost of goods sold (COGS), capital expenditure on long-term assets (CAPEX), research and development (R&D), and sales, general and administrative (SG&A). If available, Bloomberg quantifies the supplier-customer relationship value in dollars. Bloomberg provides a supplier list of every firm. For suppliers with quantified relationship value, it also specifies percentage of the firm's cost that a supplier represents (% Cost) as well as percentage of that supplier's revenue the firm makes up (% Revenue). Table 1 lists sample data obtained from Bloomberg.

One drawback of Bloomberg supply chain relationship data is that it is a static snapshot of existing supplier-customer relationships, lacking a historical perspective. The relationships are *valid*

Table 1 Sample data from Bloomberg.

Name	Country	Market Cap	Sales Surprise	% Revenue	Relationship Value	Account As Type	%Cost	Source	As Of Date
SAMSUNG ELECTRON	South Korea	200.78B	-0.0123						
APPLIED MATERIAL	United States	21.74B	-0.0404	0.2	435.95M	CAPEX	0.0804	*2012A CF	11/15/2012
JEONGMOON INFO	South Korea	42.04M	N.A.	0.26	1.77B	COGS	0.0624	2013C3 CF	11/14/2012
IMARKET KOREA INC	South Korea	818.83M	-0.0151	0.3012	163.18M	SG&A	0.0142	*2013C2 CF	7/26/2013

Notes. This table displays samples of supply data available on Bloomberg. It lists three Samsung Electron's suppliers. For each identified relationship, Bloomberg reports the relationship value, % revenue and % cost to the supplier and the customer, the data source and the as of date for the relationship.

relationships at the time (Oct to Dec 2013) of data collection by the authors, with most source dates (i.e., the date when the relationship is disclosed) between first quarter of 2012 and the first quarter of 2013. Assuming that supplier relationships are stable over short time horizons, we consider this data as representative for supply chain relationships from 2011 to 2013.

3.2. Choice of Sector

There are three reasons for our choice of the high-tech sector. First, it is among the top few sectors that reportedly faces a higher frequency of supply chain disruptions compared to others. Schmidt and Raman (2015) identify disruptions by analyzing company press releases distributed via the PRNewswire and Business Wire. According to their study, high-tech has the second largest number of disruption announcements from 1998 to 2011 among all sectors following Chemicals and Petroleum. Second, the hyper-competitive nature and rapid growth rate of the sector make firms more vulnerable to supply disruptions (Taylor 2002). The now famous Nokia Ericsson case illustrates how a fire at a supplier's plant reshaped the European mobile phone market. Ericsson's slower response to the disruption, compared to Nokia, resulted in a loss in sales of approximately \$400 million within a quarter after the disruption (Eglin 2003). Ericsson lost 3 percent market share to Nokia only 6 months after the incident. The short product life cycle, high demand variability and aggressive competition make high-tech sector a particularly interesting test-bed for the study of supply chain risks. The final reason for our choice is better data coverage. Early data collection efforts from Bloomberg were focused on the high-tech sector for similar reasons we have listed above. As a result, the high-tech sector has the most identified COGS percentage.

We use Global Industry Classification Standard (GICS) to define sectors. GICS is an industry taxonomy developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P) for the global financial community and is available on Bloomberg terminals. We label all firms in the information technology sector (GICS Code: 45-) and personal appliance sub-industry (GICS Code: 252010) as high-tech firms. We include firms in personal appliance (e.g. Sony Corp., Panasonic Corp.) nevertheless to be consistent with definitions by North American Industry Classification System (NAICS), the commonly used industry code in US market research. We restrict our attention to publicly traded firms because further empirical analysis requires knowledge of financial and operational performances of firms, unavailable for private firms.

We thus obtain around 8,000 publicly traded high-tech firms, among which 2,646 firms have quantified supplier data. The 2,646 firms account for 81 percent of the total market capitalization of the sector: the remaining firms tend to be small international firms. 67 percent of suppliers of these high-tech firms also belong to the high-tech sector. In addition, many high-tech firms also source from two other sub-industries, electrical equipment (GICS code: 201040) and machinery (201060). Therefore, to ensure accuracy and representativeness of our supply network, we also collect supplier information of firms in these sub-industries.

3.3. Data Preparation and Summary

Recall that the database classifies the nature of the supplier relationship into four categories: COGS, CAPEX, R&D, and SG&A. We first exclude relationships other than COGS, because our study focuses on risk aggregation resulting from repeated business relationships between a customer and its suppliers. Second, because most non-quantified relationships are induced from media postings instead of public filings including annual, quarterly and current reports, we exclude non-quantified relationships for higher data accuracy. The resulting network consists of 4,538 firms, including 2,646 high-tech firms and 1,890 non-high-tech firms, and 13,670 directional links indicating supplier-customer relationships. The non-high-tech firms serve as suppliers of high-tech firms and consist of firms mostly from electrical equipment and machinery sectors.

We first compare supplier coverage of Bloomberg and Compustat, a commonly used data source for constructing supply chain relationships. To conduct a fair comparison, and because all Compustat relationships are quantified, we only consider quantified relationships from Bloomberg. As shown in Table 2, for all S&P500 firms in the high-tech sector, Bloomberg on average identifies *four times more* US suppliers and *seven times more* global suppliers compared to Compustat.

We then retrieve quarterly financial and operational data for high-tech firms and their suppliers to evaluate firm performance from 2011 to 2013. The data includes stock price, market capitalization, sales, financial leverage, return on asset, book to market ratio, days in inventory and inventory growth. Firms are excluded if they are not actively listed for the study period. Performance outliers are also excluded (i.e., firms with more than three years of inventory are excluded).

Table 3 displays the summary statistics of our data. We summarize supplier coverage in Panel A and firms' financial and operational performances in Panel B. An average high-tech firm in our dataset has 5.1 suppliers quantified, who collectively contribute to 9.47% of its procurement costs (COGS). The relatively small fraction of COGS accounted for, even though higher than what could have been obtained using other data sets, underscores the challenge of identifying the supply base more completely.

Given that Bloomberg data is a superset of Compustat data, it is likely that Bloomberg, too, identifies proportionally more suppliers for US domestic firms than international firms. Moreover,

Table 2 Suppliers identified by Bloomberg and by Compustat.

Name	GICS	Market Capitalization ($Mn)	GVKEY	Ticker Symbol	# of Suppliers identified in Compustat	# of US Suppliers identified in Bloomberg	# of Suppliers identified in Bloomberg
Facebook	451010	80,175	170617	FB	3	5	10
eBay Inc.	451010	55,800	114524	EBAY	0	4	5
Yahoo Inc.	451010	23,464	62634	YHOO	2	20	25
		53,146			**2**	**10**	**13**
Microsoft Corp.	451030	247,930	12141	MSFT	12	49	93
Oracle Corp.	451030	153,645	12142	ORCL	4	14	19
Salesforce.com	451030	23,036	157855	CRM	0	6	6
		141,537			**5**	**23**	**39**
Cisco Systems	452010	105,483	20779	CSCO	20	89	118
QUALCOMM Inc.	452010	102,851	24800	QCOM	3	9	17
Motorola Solutions Inc.	452010	15,248	7585	MSI	10	71	120
		74,527			**11**	**56**	**85**
Apple Inc.	452020	442,008	1690	AAPL	10	51	120
EMC Corp.	452020	52,375	12053	EMC	9	17	18
Hewlett-Packard	452020	49,967	5606	HPQ	33	94	187
		181,450			**17**	**54**	**108**
Grand Average		**67,538**			**9**	**36**	**62**

Notes. This table lists the number of suppliers reported in Compustat and Bloomberg databases. We include all suppliers reported in Compustat in 2009 and later. To simplify the table, we include the top three (highest market capitalization) SP500 firms that stay in the listed four sub-industries.

Table 3 Summary Statistics.

Variable		Mean	Standard Deviation Overall	Between	Within	N # Firms	# Observations
Panel A							
# Suppliers	*count*	5.1	14.04			2646	
Cost Identifed	*%*	9.47	15.48			2646	
Cost Identified (US firms)	*%*	11.54	17.98			445	
Cost Identifed (OEM firms)	*%*	56.29	34.23			19	
Panel B							
Log Market Capitalization	*$Mn*	5.77	2.12	2.09	0.31	3707	39752
Financial Leverage (FL)	*ratio*	1.71	2	1.55	1.26	3748	40164
Days in Inventory (DII)	*days*	52.24	67.46	59.33	32.11	3331	34350
Inventory Growth(INGR)	*%*	8.67	39.24	18.24	34.74	3476	35658
Gross Margin(GM)	*ratio*	19.43	20.97	19.22	8.4	3532	37053
Book to Market (BTM)	*ratio*	0.7	0.84	0.72	0.43	3694	38472
Return on Asset (ROA)	*ratio*	1.13	40.63	21.76	34.33	3694	38472
Operational Margin(OM)	*ratio*	3.98	12.378	10.17	7.05	3717	39215

since Bloomberg identifies many of its supply chain relationships from public disclosures or news coverage, it is likely that large firms closer to the consumer market tend to get greater media exposure and hence have more of their suppliers identified. For example, Apple Inc. provides its entire supplier list and their plant locations directly on its website. In our data, the average cost captured for a US firm is 11.54%, as compared to 9.47% for an average firm (see Table 3). Also, the average cost captured the top 21 high-tech companies identified in IBIS Industry Research report (IBISWorld 2015), is 56.29% suggesting that a firms size and its position in the supply chain, upstream or downstream, may affect the proportion of its suppliers identified. We address resulting coverage bias issues next.

3.4. Assessment of Coverage Bias

Understanding what types of firms are more (or less) likely to have their supplier information identified in the dataset is critical to assessing the impact of potential coverage bias on the estimation results. In this section, we conduct several tests to examine the existence and magnitude of potential coverage bias by country of origin, supply chain upstream and downstream positions (as reflected by detailed industry code), and firm size.

It is reasonable to expect that each firm in the high-tech sector sources from at least one supplier. We therefore use the percentage of having at least one supplier identified to evaluate what types of firms are more (or less) likely to have biases in their supplier coverage. Table 4 demonstrates how this measure varies across sub-industries and countries of origin. In each cell, we report the number of firms and the percentage of firms with at least one supplier identified.

Table 4 Coverage Bias.

At least one supplier identified by countries of origin and sub-industries

Country\GICS	252010 Household Durables	451010 Internet Software & Services	451020 IT Services	451030 Software	452010 Communi-cations Equipment	452020 Computers & Peripherals	452030 Electronic Equipment & Components	453010 Semicon-ductors	All High-Tech
US	15	41	37	72	61	37	94	107	464
	(0.73)	(0.71)	(0.78)	(0.71)	(0.84)	(0.84)	(0.82)	(0.77)	(0.78)
Japan	18	22	72	64	16	27	162	53	434
	(0.78)	(0.64)	(0.90)	(0.59)	(0.94)	(0.85)	(0.90)	(0.79)	(0.82)
Korea	13	7	19	15	19	10	68	92	243
	(0.92)	(0.86)	(0.89)	(0.53)	(0.68)	(0.80)	(0.68)	(0.68)	(0.71)
China	29	4	22	21	41	19	85	40	261
	(0.79)	(0.75)	(0.59)	(0.71)	(0.76)	(1.00)	(0.72)	(0.88)	(0.77)
Taiwan	18	1	10	9	33	82	200	189	542
	(0.89)	(1.00)	(0.80)	(0.89)	(0.97)	(0.91)	(0.88)	(0.91)	**(0.89)**
Other	33	10	78	63	36	24	111	56	411
	(0.94)	(0.80)	(0.77)	(0.79)	(0.75)	(0.96)	(0.77)	(0.77)	(0.80)
All Locations	126	85	238	244	206	199	720	537	2355
	(0.85)	(0.72)	(0.81)	(0.70)	(0.82)	**(0.90)**	(0.82)	(0.81)	(0.81)

Notes. The number of firms in the related region and sub-industry is reported in each cell. Underneath, we report the percentage of firms that have at least one supplier identified in Bloomberg dataset.

We find that firms operating in Taiwan and firms in the sub-industry Household Durable or Computer & Peripherals are more likely to have at least one supplier identified in the data; that is, these firms are likely to have more complete supplier information. Note that as compared to other sub-industries such as semiconductor and IT services, these two sub-industries are closer to the consumer market. We refer to the two sub-industries, Household Durable or Computer & Peripherals, as "close-to-market" sub-industries. We also observe that larger firms tend to have better supplier coverage: at \$2,014 million, the average annual sales of firms with at least one supplier identified is more than five times that of firms with no identified suppliers. We use a probit model to assess the impact of all three factors, country of origin, sub-industry code and firm size, on the likelihood of having at least one supplier being identified (see Appendix Table A1). The estimates confirm our previous conclusions. The results are also consistent when we change the cutoff to at least five suppliers identified. These patterns provide the basis for our sub-sample robustness tests to verify that our main results are not driven by the coverage bias.

4. Empirical Model

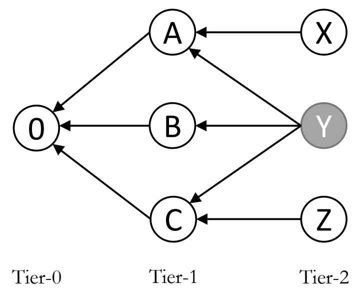
We propose several metrics to quantify the degree of tier-2 sharing, and discuss the risk measure we use to characterize firm risks. Based on these metrics, we describe the empirical models and interpret the model estimates.

4.1. Measures of Tier-2 Commonality

We introduce three metrics of tier-2 commonality : 1) degree of commonality, 2) diamond ratio and 3) cosine commonality score. The first two metrics are based on the binary customer-supplier relationship, while the third metric is based on customer-supplier relationship weighted by the percentage of costs that a supplier represents. We construct both un-weighted and weighted measures of tier-2 commonality because it is unclear how sub-tier commonality affects risk. On the one hand, one may expect a larger supplier, who represents a significant portion of the customer's COGS, to likely have a larger impact on the customer's performance. Partially due to the lack of a better measure to account for component criticality or the network location of a supplier, cost percentage as a proxy for supplier significance has been used in theoretical papers that study how economic fluctuations aggregate (Acemoglu et al. 2012) and empirical papers that study relationships between supplier and customer returns (Menzly and Ozbas 2010). On the other hand, many supply chain disruptions have routinely been reported to be caused by suppliers who account for only a small portion of COGS, but constitute a major threat when impacted. For example, consequent to the Japan earthquake and tsunami in 2011, shortage of components from the shared sub-tier suppliers, like Renesas (chip supplier) and Merck (paint pigment supplier), caused month-long production delays for the automotive manufacturers (Kyodo 2011, Sedgwick 2014). Despite the small cost percentage of these components, disruptions at Renesas and Merck propagated to manufactures owing to the component non-substitutability. Thus, the share of overall COGS may or may not be a major driver of sub-tier supply risks. Hence, we introduce both cost-weighted and non-cost-weighted measures for tier-2 commonality, and test their impacts in subsequent sections.

4.1.1. Degree of Commonality: We measure the degree of tier-2 supplier commonality as follows. Consider the simple two-tier supply network depicted in Figure 1, in which Firm 0 has three tier-1 suppliers, labeled A, B, and C, and three tier-2 suppliers, labeled X, Y and Z. Note

Figure 1 **Illustration of common tier-2 supplier with degree of tier-2 commonality** $k = 3$**.**



that supplier Y is shared by all tier-1 suppliers, while suppliers X and Z are not shared. The degree of sharing of a tier-2 supplier is reflected by the number of paths that connect the tier-0 firm to the tier-2 supplier. In this figure, there are three paths from the tier-0 firm to the tier-2 firm Y, while only one path from the tier-0 firm to X and Z, respectively. A tier-2 supplier is considered shared if there is more than one path that links a tier-0 firm to that tier-2 supplier.

We now define the pair-wise degree of commonality as the number of paths that link every pair of a tier-0 firm and a tier-2 supplier. To obtain an aggregate measure of degree of commonality for the tier-0 firm, we take the average of the pair-wise degree of commonality of all pairs of tier-0 and tier-2s. In Figure 1, the aggregate degree of commonality of the tier-0 firm is $(1 + 3 + 1)/3 = 1.66$, which indicates that an average tier-2 supplier of the focal tier-0 firm is shared by 1.66 tier-1 suppliers. Thus, a degree of commonality equal to 1 indicates no sharing through tier-1 suppliers, while a value greater than 1 indicates existence of sharing through the corresponding number of tier-1 suppliers.

4.1.2. Diamond Ratio: While degree of commonality is an intuitive measure indicating the number of tier-1 suppliers that share a tier-2 supplier, the measure is influenced by the number of tier-1 suppliers that a firm has. That is, a tier-0 firm with more tier-1 suppliers is more likely to have a higher degree of commonality. This may introduce a bias between the degree of commonality and firm size because a large firm with higher number of identified immediate suppliers will tend to have a higher degree of commonality. To address this potential issue we propose another metric, diamond ratio, which normalizes the degree of commonality with the size of the tier-1 supply base.

Specifically, the diamond ratio of each tier-0 firm is obtained by dividing the degree of commonality by the number of tier-1 suppliers. This metric also has an alternative intuitive interpretation. One can view the diamond ratio as the number of observed tier-0 to tier-2 paths over the number of all possible paths in a firm's supply network. Note that the number of all possible paths is precisely the product of the number of tier-1 suppliers and the number of tier-2 suppliers. For example, the diamond ratio of the tier-0 firm in the supply network depicted in Figure 1 equals $5/(3 \times 3) = 0.56$. By definition, the diamond ratio can only take a value between 0 and 1, and a higher value indicates the presence of more common tier-2 suppliers.

4.1.3. Cosine Commonality Score: Our third measure, cosine commonality score, considers cost weighted supplier-customer relationships. First, we define the cost percentage matrix C where C_{ij} denotes the percentage of customer firm j's COGS contributed by firm i. Let matrix A denote the binary customer-supplier relationship, namely $A_{ij} = \mathbf{1}(C_{ij} > 0)$. The rows of C and A are indexed by supplier firms and the columns are indexed by customer firms. If the supplier-customer relationship data is complete, the column sum of C should be 1, as the data identifies the entire allocation of COGS among a firm's supply base. Using matrices C and A, we define the Cosine Commonality Score (CCS) of firm i as

$$\mathrm{CCS}_i \;=\; \underset{j\neq m, A_{ji}=A_{mi}=1}{\mathrm{median}} \cos(C_{\cdot,j}, C_{\cdot,m}) \;=\; \underset{j\neq m, A_{ji}=A_{mi}=1}{\mathrm{median}} \frac{\langle C_{\cdot,j}\ , C_{\cdot,m}\rangle}{\|C_{\cdot,j}\|_2\ \|C_{\cdot,m}\|_2}$$

where $C_{\cdot,j}$ is the jth column of C. $\cos(C_{\cdot,j}, C_{\cdot,m})$ represents the pair-wise cosine similarity between the cost distributions of tier-1 supplier j and m. Cosine similarity measures the cosine of the angle between two vectors of an inner product space. The cosine similarity between any two firms ranges from 0 to 1, where 0 indicates no shared supplier, and 1 indicates that two firms have the exact same supply base: same suppliers and same spend. We then aggregate the pair-wise measure for the tier-0 firm over all pairs of its tier-1 suppliers. We choose median (rather than mean) among all the pair-wise cosine similarities because of the high skewness of the distribution of cosine similarities. Similar to the diamond ratio, a higher value of cosine commonality score suggests the presence of more tier-2 sharing.

4.2. Risk Measure

4.2.1. Firm Risk Ideally, we can construct firm risk from its operational performance. However, due to the unobservability of operational impact and the lack of facility-level data, we opt for the next best alternative of evaluating firm risk based on its financial performance. Given the close link between a firm's financial and operational performances, we believe that the association of sub-tier suppliers and tier-0 firms introduced by supply chain relationships will also be reflected in the association of their financial performances.

Stock return volatility, often referred to as firm total equity risk, is our dependent variable. It is measured by the variance of the rate of return of the firm's equity over a certain time period. In this study, we use a three-month time window. The total equity risk of firm i in quarter t, $\mathrm{VOL}_{it} = \mathrm{Var}(R_{id}), d \in t$, where R_{id} represents daily return on day d. The variance of equity return has been widely used as a measure of firm total risk in previous research (e.g., May 1995, Guay 1999, Hendricks and Singhal 2005b). Because VOL_{it} is a measure that takes only positive values, we use its logarithm, denoted as vol_{it}, in subsequent regression analyses.

Asset pricing models suggest that a firm's total equity risk is affected by both systematic risks and idiosyncratic risks. Systematic risks refer to risks that cannot be eliminated by diversification. For example, all equities take on certain levels of, albeit different, market risk that are non-diversifiable. Idiosyncratic risk refers to the risk that can be avoided through a diversified portfolio. For example, the risk of a plant shut-down due to floods can be mitigated by investing in firms located in non-flood prone regions. There are reasons to believe that supply chain linkages contribute to both systematic and idiosyncratic risks. Even though a supply chain disruption is typically considered firm-specific and therefore should contribute only to the idiosyncratic risk that a firm is exposed to, recent studies conjecture that supply network structure may be a source of systematic risks. Acemoglu et al. (2012) argue that microeconomic idiosyncratic shocks can lead to aggregate fluctuations through inter-sectoral input-output linkages. Even though the model they propose is not an asset pricing model, it lays the foundation for why idiosyncratic risks may aggregate to become a systematic risk. A more recent study by Ahern (2013) finds that connectivity to suppliers explains why the more central firms take on greater levels of systematic risks. Therefore, instead of isolating systematic risk from the total risk, we decide to use the total risk as our dependent variable. Furthermore, it is beyond the scope of this paper to establish supply network as a factor in asset pricing models or to evaluate its asset pricing implications.

4.2.2. Supplier Risks To test the impact of suppliers on tier-0 firm risk, we aggregate suppliers' risks by tier. We follow Menzly and Ozbas (2010) to create portfolios of supplier firms and weight each supplier using a normalized cost percentage, from the perspective of a tier-0 firm. For example, if a firm has only two identified tier-1 suppliers, and spends an equal amount between the two to acquire necessary inputs from them, we compute the tier-1 supplier risk as the average of the stock return volatilities of the two suppliers. For a tier-0 firm i, we let SPL_vol_{it} denote tier-1 supplier risk, and T2SPL_vol_{it} denote tier-2 supplier risk in quarter t.

$$\text{SPL\_vol}_{it} = \frac{\sum_j C_{ji} \times \text{vol}_{jt}}{\sum_j C_{ji}}, \quad \text{and} \quad \text{T2SPL\_vol}_{it} = \frac{\sum_j [C^2]_{ji} \times \text{vol}_{jt}}{\sum_j [C^2]_{ji}}. \tag{1}$$

C_{ji} represents the percentage of firm i's cost attributed to supplier j, and $\sum_j C_{ji}$ is the total percentage of COGS of firm i identified. C^2 is the squared matrix of C, where $[C^2]_{ji} = \sum_k C_{jk} C_{ki}$ is the percentage of firm i's cost attributed to its tier-2 supplier j. In addition to the aggregate risk measures at each tier, we are particularly interested in risks originating from common tier-2 suppliers. Let $\text{T2COMSPL\_vol}^k_{it}$ denote risks of those tier-2 suppliers that are shared by at least k tier-1 suppliers. It can be computed as the weighted risks of common tier-2 suppliers of firm i in quarter t with at least k degree of tier-2 commonality.

$$\text{T2COMSPL\_vol}^k_{it} = \frac{\sum_{j:[A^2]_{ji} \geq k} [C^2]_{ji} \times \text{vol}_{jt}}{\sum_{j:[A^2]_{ji} \geq k} [C^2]_{ji}}. \tag{2}$$

Recall that matrix A is the binary indicator matrix of supplier-customer relationship, namely $A_{ij} = \mathbf{1}(C_{ij} > 0)$. $[A^2]_{ji}$ is the pair-wise degree of commonality of supplier j in firm i's supply network, and $[A^2]_{ji} \geq k$ denotes the set of tier-2 suppliers that are shared by at least k tier-1 suppliers.

4.3. Other Independent Variables

There are other factors that can potentially affect firm risk. Firm size measured by the logarithm of a firm's net sales in the previous twelve months, and financial leverage measured by the total asset over common stock equity ratio, are two important determinants of firm equity risk (Ben-Zion and Shalit 1975). Additionally, following Schmidt and Raman (2015) we also include firm profitability as a factor influencing firm risk. Return on assets, operating margin, and gross margin are three measures of firm profitability. Due to collinearity, we only include return on assets in the regression and our results are robust to alternative measures of profitability.

Firm equity risk is also affected by the amount of inventory that a firm holds. The supply chain literature has long studied the role of inventory as a buffer against uncertain supply and demand (e.g., Ritchken and Tapiero 1986, Chen et al. 2007, Hopp et al. 2008). Using data from publicly listed US retailers, Alan et al. (2014) find that inventory productivity can predict future stock returns. We include both inventory level (days in inventory) and inventory growth rate in our explanatory variables. Holding everything else constant, firms with higher inventory levels are better able to buffer supply and demand uncertainties. Inventory growth rate is associated with future firm performance, and hence firm risks; higher inventory growth rates may either indicate excess supply relative to realized demand or an expectation of faster growth. Inventory held by suppliers also reduce supply risks faced by their customers. Therefore, we also control for tier-1 suppliers' inventory level by taking a COGS weighted average of each supplier's inventory level.

We also control for the quarterly volatility of a firm's trading market. We obtain index performances for the following trading markets, United States (SPX Index), Japan (NKY Index), Korea (KOSPI Index), Taiwan (TWOTCI Index), Mainland China (SHASHR Index), France (CAC Index), India (SENSEX Index), Hongkong (HSI Index), United Kingdom (UKX Index) and Germany (DAX Index). Firms in our data are traded in 60 different markets. We estimate a fixed effect using a small trading market dummy for the firms traded in the other markets — each contains less than 1% of firms in our sample. Multinational firms do not necessarily trade in countries of their main business locations, so we create dummy variables for firms' headquarter locations as well. A firm's stock performance can be influenced by the volatility intrinsic to a trading market and the level of economic uncertainties in the country of operation. The geographic distribution of firms' operating locations in our sample is as follows, Japan (20%), United States (19%), Taiwan (16%), Mainland China(14%), and South Korea (10%). We group firms operating in other origins as "other" in our regression analyses. Sub-industry dummies for every 6-digit GICS code are included as well to control for industry specific risks.

4.4. Model Specification

Our dependent variable is the logarithm of a firm i's stock price volatility in quarter t, vol_{it}. Variables of interest are tier-2 supplier risk, common tier-2 supplier risk, and the measure of sub-tier network structure, diamond ratio (DMD) and cosine commonality score (CCS). Other independent variables include market risk (MKT_vol_{it}), tier-1 supplier risk (SPL_vol_{it}), and financial and operational characteristics denoted by matrix X_{it}. X_{it} contains firm i's days in inventory, inventory growth rate, firm size, financial leverage, book-to-market ratio, return on asset, and weighted supplier days in inventory in quarter t. Vector D_i contains the headquarter location dummies and the sub-industry dummies.

$$\text{vol}_{it} = \alpha_0 + \quad + \alpha_1 \text{MKT\_vol}_{it} + \alpha_2 \text{SPL\_vol}_{it} + X_{it}\gamma + D_i\phi + \epsilon_{it} \tag{3}$$

$$\text{vol}_{it} = \alpha_0 + \beta_1 \text{T2SPL\_vol}_{it} + \alpha_1 \text{MKT\_vol}_{it} + \alpha_2 \text{SPL\_vol}_{it} + X_{it}\gamma + D_i\phi + \epsilon_{it} \tag{4}$$

$$\text{vol}_{it} = \alpha_0 + \beta_2^k \text{T2COMSPL\_vol}_{it}^k + \alpha_1 \text{MKT\_vol}_{it} + \alpha_2 \text{SPL\_vol}_{it} + X_{it}\gamma + D_i\phi + \epsilon_{it} \tag{5}$$

$$\text{vol}_{it} = \alpha_0 + \beta_3 \text{T2SPL\_vol}_{it} + \beta_4 \text{DMD}_i + \alpha_1 \text{MKT\_vol}_{it} + \alpha_2 \text{SPL\_vol}_{it} + X_{it}\gamma + D_i\phi + \epsilon_{it} \tag{6}$$

$$\text{vol}_{it} = \alpha_0 + \beta_3 \text{T2SPL\_vol}_{it} + \beta_4 \text{CCS}_i + \alpha_1 \text{MKT\_vol}_{it} + \alpha_2 \text{SPL\_vol}_{it} + X_{it}\gamma + D_i\phi + \epsilon_{it} \tag{6'}$$

Equation 3 is the base model excluding variables of interest. Equation 4 adds the tier-2 supplier risk and tests Hypothesis 1. We anticipate a positive β_1, which indicates a positive association between tier-2 supplier risk and the tier-0 firm's risk. Equation 5 estimates the impact of common tier-2 suppliers on the tier-0 firm's risk, which tests Hypothesis 2. We expect β_2^k to be positive and increases as the degree of commonality k increases. Equation 6 tests Hypothesis 3. It separates the impact of tier-2 supplier risk and sub-tier network structure on the tier-0 firm's risk. We again expect a positive coefficient for tier-2 supplier risks, β_3. We also anticipate a positive effect of the diamond ratio (DMD) and cosine commonality score (CCS). That is, a supply network with larger overlapping in tier-2 suppliers leads to higher tier-0 firm risk. In addition to the direction, we are also interested in the scale of the coefficients, especially their magnitude relative to coefficients of the market risk, α_1, and of tier-1 supplier risk, α_2.

4.5. A Note on Causality

We make a note on the causal implication of these estimates. Coefficients of supplier risks, α_2 (tier-1 supplier risks), $\beta_1, \beta_2^k, \beta_3$ (tier-2 or common tier-2 supplier risks) should not be interpreted as causal for two reasons. First, firms engage in various risk management activities to mitigate risks arising from suppliers. For example, besides building inventory buffers (which we control for), firms also use multiple sourcing and flexible capacity to mitigate the impact of potential supply chain disruptions. Existence of these unobserved firm decisions, which are correlated with both supplier risks and the firm's risk, will generate omitted variable bias in estimating the impact of supplier risks. This is not only true for the coefficients of tier-1 supplier risk, but also true for the coefficients of tier-2 supplier risk. Even though the tier-0 firms typically do not take actions directly in response to tier-2 supplier risks due to lack of visibility, risk mitigation actions taken by tier-1 suppliers can also contribute to the omitted variable bias. Tier-1 suppliers may take risk mitigation actions according to the level of risks coming from tier-2. Meanwhile, such activities at tier-1s can help tier-0 firms mitigate supply disruptions — even though we control for tier-1 supplier inventory, other firm decisions are unobserved. Such bias, however, tends to be a downward bias, which can be in favor of our analysis because we expect a positive sign.

Second, in addition to supply shocks that propagate downstream, demand shocks that propagate upstream can also contribute to the observed correlation between the tier-0 firm's risk and its suppliers' risks, such as in the bullwhip effect (Bray and Mendelson 2012). This reverse causality can also bias the estimates, likely in the upward direction. Identifying exogenous supply shocks may address both biases. However, collecting a sufficiently large number of supply shocks that impact a broad cross-section of firms is beyond the scope of this paper (Wu 2015).

Even though the coefficients of supplier risks cannot be interpreted as causal, we believe that the impact of network structure, and in particular the sub-tier structure, is most likely causal. First, firms typically do not have visibility into tier-2 suppliers, nor the contractual power to dictate who their tier-1 suppliers should or should not source from. As a result, it is unlikely firms will be capable of taking actions in response to sub-tier supplier commonality. Second, in wake of the Japan earthquake and tsunami in 2011 even though a few large manufacturing firms have discovered overlapping sub-tier structure in their supply network, the process of mapping out sub-tier suppliers has just begun and firms are not fully aware of its extent and impact, let alone taking systematic actions to address the issue. Third, even though tier-1 suppliers contract directly with tier-2 suppliers, tier-1s are typically unaware of other tier-1s. This makes it impossible for tier-1 suppliers to take any collective action to avoid overlaps in their supplier bases either. In sum, due to the limited visibility into supply chain network from both the tier-0 and tier-1 firms and the lack of direct influence from the tier-0 firm, the estimated impact of tier-2 commonality, diamond ratio and cosine commonality score in Equation 6 is most likely a causal impact.

5. Empirical Results

We first describe the basic network properties of our high-tech supply network and demonstrate the prevalence of common tier-2 suppliers. We then show how tier-2 supplier commonality affects tier-0 firm risk.

5.1. Tier-2 Commonality

In our network, an average high-tech firm is connected to three suppliers and three customers. This network, though sparse, turns out to be highly connected. The network involves a few complete disjoint subnetworks (components), and the largest connected component of the supply network, in which any two firms are connected to each other by undirected paths, contains around 95% of all firms. The average length of the shortest paths between any two firms within the component is 3.93. As we are interested in the impact of tier-2 supplier commonality, for further analysis, we focus our attention to the 4,253 firms in the largest connected component.

Table 5 shows summary statistics of all three measures of tier-2 commonality, 1) degree of commonality, 2) diamond ratio, and 3) cosine commonality score. We find that the median degree of commonality of all tier-0 high-tech firms is 1.05, suggesting that more than half of the firms have common tier-2 suppliers in their supply networks. Using degree of commonality, we identify

Table 5 Statistics of tier-2 commonality measures.

	Degree of Commonality	Diamond Ratio	Cosine Commonality
Mean	1.160	0.297	0.048
Standard Deviation	0.251	0.181	0.130
.25 percentile	1.000	0.150	0.000
Median	1.068	0.289	0.000
.75 percentile	1.230	0.500	0.017
.95 percentile	1.690	0.550	0.297

Notes. Statistics are computed for high-tech firms that have at least two suppliers reported .

tier-2 firms that are heavily shared and also tier-0 firms whose supply network involves most tier-2 sharing. Table 6 lists all tier-2 firms who are shared by a large number of tier-1 suppliers, i.e., greater than or equal to 20, in any tier-0 firm's network. Most of the heavily shared tier-2 suppliers are semiconductor companies. Numbers in the final column of the table represent the number of tier-0 firms that source from these tier-2 suppliers. Our data also indicates that these tier-2 suppliers are not necessarily immediate suppliers of the associated tier-0 firm, implying that without sub-tier visibility, firms may not realize that they rely on a particular set of sub-tier suppliers. For instance, 20 of Dell's tier-1 suppliers and 24 of HP's tier-1 suppliers source from Stats Chippac Ltd., who does not directly supply to any of the S&P500 hardware manufacturers.

Table 7 lists all tier-0 firms whose supply network relies on these heavily shared tier-2 firms. Most of them are in the Technology Hardware & Equipment industry (GICS code: 4520x). The table also indicates that many tier-2 suppliers are shared in these firms' supply networks — 35% are shared by at least two tier-1 suppliers, and more than 10% are shared by at least five tier-1s.

Table 6 Tier-2 suppliers with a high degree of tier-2 commonality.

Tier-2 Supplier Name	GICS	Headquarter Location	# of tier-0 firms that source from the listed tier-2 supplier who is shared by at least 20 of their tier-1 suppliers
Flextronics International Ltd.	452030	USA	2
Avago Technologies	453010	Singapore	2
Microsoft Corporation	451030	USA	2
Nitto Denko Corporation	151010	Japan	1
Atmel Corporation	453010	USA	1
Intel Corporation	453010	USA	3
LSI Corporation	453010	USA	2
Qualcomm Inc.	452010	USA	2
Texas Instruments Inc.	453010	USA	6
United Microelectronics Corporation	453010	Taiwan	4
ON Semiconductor	453010	USA	2
Advanced Semiconductor Engineering Inc.	453010	Taiwan	8
Taiwan Semiconductor Ltd.	453010	Taiwan	13
Amkor Technology Inc.	453010	USA	11
ARM Holdings plc	453010	Great Britain	11
Broadcom Corporation	453010	USA	2
STATS ChipPAC Ltd.	453010	Singapore	5
NXP Semiconductors	453010	Netherlands	1

Table 7 Tier-0 firms with common tier-2 suppliers.

Name	GICS	Headquarter Location	Market Capitalization ($Mn)	# of tier-2s identified	# of tier-2s shared by at least **two** tier-1s	# of tier-2s shared by at least **five** tier-1s	# of tier-2s shared by at least **twenty** tier-1s
Cisco Systems, Inc.	452010	USA	105,483	523	195	53	3
Dell Inc.	452020	USA	25,465	847	340	114	6
Hewlett-Packard Company	452020	USA	49,967	865	357	123	8
LG Electronics Inc.	252010	South Korea	10,776	799	321	83	4
Apple Inc.	452020	USA	442,008	889	333	110	3
Samsung Electronics Co., Ltd.	453010	South Korea	143,504	956	346	105	6
Sony Corporation	252010	Japan	19,422	816	282	73	2
IBM Corporation	451020	USA	214,975	853	331	106	1
Lenovo Group Ltd.	452020	China	8,708	838	333	91	1
WPG Holdings Ltd.	452030	Taiwan	2,141	652	225	49	3
Avnet, Inc.	452030	USA	4,799	720	286	88	6
Arrow Electronics Inc.	452030	USA	4,274	926	366	122	6
Ingram Micro	452030	USA	2,890	1100	481	198	12
Nokia Corporation	452020	Finland	18,864	675	225	53	4
Alcatel-Lucent S.A.	452010	France	6,584	418	150	34	1
Ericsson	452010	Sweden	36,616	638	188	44	1
Motorola Solutions, Inc.	452010	USA	15,248	619	190	32	2
Tech Data Corporation	452030	USA	2,008	1099	435	173	9

5.2. Impact of Tier-2 Commonality

We estimate Equations 3, 4 and 5 using fixed effects models to account for potential unobserved firm characteristics, which can also be correlated with other covariates. For example, firms with higher supply risks are more likely to use flexible capacity, which in turn reduces risks. The use of fixed effect models eliminates the bias coming from time-invariant firm characteristics. When we are interested in the coefficient of sub-tier network structure measures, namely the diamond ratio and cosine commonality score, fixed effects models are no longer valid because fixed effects will absorb the effects of time-invariant sub-tier network structure. Instead, we use a random effects model. The coefficients of sub-tier network structure are likely unbiased, because unobserved firm activities are not correlated with tier-2 supplier commonality as discussed in Section 4.5.

Table 8 provides the model estimates. Column (a) shows the estimates for the base model in Equation 3 with no tier-2 related variables. As expected, the market risk explains most variations in the firm's total risk. The positive significant coefficient of tier-1 supplier risk is consistent with previous research, confirming that customer and supplier share correlated risks through their relationship. The signs of the estimates of other covariates are consistent with the literature as well. As a reflection to the risk of debt and overvalued stock prices, firms with higher leverage and lower book-to-market ratio experience higher stock return volatility. We also find that days of inventory of immediate suppliers is negatively associated with the risk of tier-0 firms. On average, a firm's stock return volatility reduces by 3.7% when its suppliers' inventory doubles.

Table 8 Common tier-2s

DEPENDENT VARIABLE: Log Volatility	(a) Base Case	(b) Tier-2	(c) Tier-2 shared by ≥ 2 Tier-1s	(d) Tier-2 shared by ≥ 3 Tier-1s	(e) Tier-2 shared by ≥ 4 Tier-1s	(f) Tier-2 shared by ≥ 5 Tier-1s
Tier-2 Supplier Risk		0.025				
		(0.021)				
Common Tier-2 Supplier Risk			0.017	0.035	0.098***	0.197***
			(0.023)	(0.028)	(0.033)	(0.048)
Market Risk	0.463***	0.459***	0.461***	0.461***	0.460***	0.459***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Tier-1 Supplier Risk	0.061***	0.057***	0.060***	0.059***	0.058***	0.056***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Financial and Operational controls	Yes	Yes	Yes	Yes	Yes	Yes
Missing controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,848	25,848	25,848	25,848	25,848	25,848
Number of Firms	2,277	2,277	2,277	2,277	2,277	2,277
R-squared	0.7147	0.7148	0.7148	0.7148	0.7149	0.7152

Notes. Robust cluster-adjusted standard errors are shown in parenthesis. All the covariates are included with log transformation. The overall R-squared value is reported in all columns. To simplify the table, we do not report on controls. *** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.

Column (b) reports the estimates of Equation 4, including the tier-2 supplier risk. The coefficient of tier-2 supplier risk is positive yet not statistically significant at 0.1 level. We note that this coefficient measures the average effect of tier-2 supplier risk and does not account for the heterogeneity among tier-2 suppliers. We are particularly interested, however, in the effects of common tier-2 suppliers. We estimate Equation 5 for different degrees of commonality, $k = 2,3,4$ and 5. The estimates are shown in Column (c) to Column (f). We observe that both the magnitude and significance of the estimates increase with the degree of commonality.

We note that the coefficients of market risk, tier-1 supplier risk, (common) tier-2 supplier risk are at comparable scales. The coefficients of common tier-2 supplier risk become larger than that of tier-1 supplier risk when the degree of commonality is greater than or equal to 4. In particular, when a tier-2 supplier is shared by five or more tier-1 suppliers, a 10% increase in tier-2 supplier risk is associated with 1.97% increase in the risk of the tier-0 firm. Note that even though only 2.3% of tier-2 suppliers are shared by five or more tier-1s, the impact of these small numbers of heavily shared tier-2s is almost half the size of the impact of the market (4.59%). The results can also be interpreted in terms of changes in standard deviations. When $k = 5$, one standard deviation increase in the common tier-2 supplier risk is associated with an increase of 0.79 standard deviation in a tier-0 firm's risk. Note that the results in terms of changes in standard deviations are evaluated at the mean value. In summary, our results show strong support for Hypothesis 2, though only mild (not statistically significant) support for Hypothesis 1.

Table 9 Sub-tier supply network

DEPENDENT VARIABLE: Log Volatility	(a) Base Case	(b) Tier-2	(c) Diamond Ratio	(d) Tier-2 & Diamond Ratio	(e) Cosine Commonality	(f) Tier-2 & Cosine Commonality
Tier-2 Supplier Risk		0.025		0.037*		0.037*
		(0.021)		(0.021)		(0.021)
Diamond Ratio			0.378***	0.384***		
			(0.126)	(0.126)		
Cosine Commonality					0.371***	0.374***
					(0.140)	(0.141)
Market Risk	0.463***	0.459***	0.462***	0.456***	0.462***	0.456***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Tier-1 Supplier Risk	0.061***	0.057***	0.070***	0.064***	0.070***	0.064***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Financial and Operational controls	Yes	Yes	Yes	Yes	Yes	Yes
Country, Sector controls	N/A	N/A	Yes	Yes	Yes	Yes
Missing controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	No	No	No	No
Observations	25,848	25,848	25,848	25,848	25,848	25,848
Number of Firms	2,277	2,277	2,277	2,277	2,277	2,277
R-squared	0.7147	0.7148	0.2490	0.2501	0.2511	0.2524

Notes. Robust cluster-adjusted standard errors are shown in parenthesis. All the covariates are included with log transformation except for the sub-tier network measures. Column (c) to Column (f) are estimated with REs. To simplify the table, we do not report on controls.
*** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.

To formally test how sub-tier network structure affects firm risk (Hypothesis 3), we estimate Equation 6 using two measures of tier-2 commonality. In Table 9, columns (c) and (d) display the estimates using the diamond ratio, while columns (e) and (f) report the estimates using the cosine commonality score. We repeat the results from columns (a) and (b) in Table 8 for easy comparison. We observe consistent estimates on most variables across all models, albeit using the random effects model as opposed to the fixed effects model. The coefficient of the diamond ratio is significant at 0.01 level, and it suggests a 6.9% or 0.58 standard deviation increase in tier-0 risk if the diamond ratio increases by one standard deviation. Similar results are found for the alternative measure, the cosine commonality score. The estimate is significant at 0.01 level as well, and one standard deviation increase in the cosine commonality score leads to 4.8% or 0.41 standard deviation increase in tier-0 risk. The inclusion or exclusion of tier-2 supplier risk in the model does not change the magnitude and the significance of the estimates of both sub-tier network measures, suggesting that the network measure is indeed orthogonal to tier-2 supplier risk. Thus, we find support for Hypothesis 3.

6. Robustness Tests

6.1. Subsample analysis

We demonstrated in Section 3.3 that firm size, headquarter location and the sub-industry a firm belongs to may bias the completeness of supplier data. In particular, we notice that the quality of supply information is best for large consumer electronics and computer firms (GICS code: 252010 or 452020) and for firms operating in US and Taiwan. Therefore, we test our models on the following four subsamples: 1) large firms — firms with average monthly market capitalization greater than 75 percentile in the complete sample; 2) close-to-market firms — firms in the sub-industries of consumer electronics and computers; 3) large close-to-market firms; and 4) US and Taiwan firms.

The results are shown in Table 10. For easy comparison, we repeat the original full sample estimates in column (a). Panel A shows the subsample estimates for common tier-2 supplier risks in Equation 5. Panel B and C show the subsample estimates for sub-tier network measures, diamond ratio and cosine commonality score, in Equation 6. In Panel A, the estimates have similar magnitude, and are significant in all subsample tests but one, column (c) close to market firms. However, once we further restrict our attention to large close-to-market firms, the impact of common tier-2 suppliers remain significant and with a larger magnitude than in the full sample estimate.

Similar results can be seen in Panel B. The impact of the diamond ratio is consistently estimated across all subsamples. Estimates are significant in all subsample tests but one, viz., column (b) large firms. We note that the subsample of large firms contains proportionally more semiconductor firms and electrical equipment firms, which tend to be at the upstream end of their supply chains. Supplier information tends to be less complete for such firms. Once we restrict our attention to large close-to-market firms alone, the estimate again becomes significant, and larger than in the

Table 10 Subsample tests

DEPENDENT VARIABLE: Log Volatility	(a) All samples	(b) Large Firms	(c) Close-to-Market Firms	(d) Large Close-to-Market Firms	(e) Taiwan or US Firms
Panel A. Common tier-2s					
Common Tier-2 Supplier Risk (shared by>=5 Tier-1s)	0.197***	0.197***	0.089	0.285**	0.186***
	(0.048)	(0.072)	(0.098)	(0.138)	(0.054)
Panel B. Sub-tier supply network (diamond ratio)					
Diamond Ratio	0.384***	0.128	0.787**	1.681**	0.549***
	(0.126)	(0.232)	(0.314)	(0.686)	(0.193)
Panel C. Sub-tier supply network (cosine commonality)					
Cosine Commonality	0.374***	0.167	0.346	0.541	0.272
	(0.141)	(0.186)	(0.347)	(0.378)	(0.244)
All Panels					
Observations	25,848	3,627	4,529	861	10,932
Number of Firms	2,277	315	383	72	963

Notes. Robust cluster-adjusted standard errors are shown in parenthesis. All the covariates are included with log transformation except for the network measures. To simplify the table, we do not report on market risk, tier-1 supply risk, financial and operational covariates, country, sector and missing controls. *** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.

full sample estimate. In Panel C, we observe that the cosine commonality score estimate is also at similar levels of magnitude across all subsample tests, but with low significance level.

We conclude that common tier-2 supplier risk is strongly correlated with tier-0 firm risk, and that sub-tier network measure, in particular the diamond ratio, affects tier-0 firm risk. We also note that the impact may vary across different subsamples (either due to data coverage bias or heterogeneity). In particular, the impact is most profound for large and downstream firms. We also note that, among the two sub-tier network measures, the significance of the diamond ratio tends to be more robust than that of the cosine commonality score. While the diamond ratio measures tier-2 commonality without weights, the cosine commonality score is weighted by COGS percentage. This evidence suggests that COGS percentage contributed by suppliers may not necessarily be a strong indicator of its impact on a tier-0 firm's risk, but a structural measure of commonality (like the diamond ratio) is.

6.2. Tier-1 Supplier Concentration

It is possible that firms with tier-1 suppliers located in geographical proximity or from the same sub-industry are more likely to have common tier-2 suppliers. Additionally, firms also tend to source with suppliers that belong to compatible sub-industries. That is, the level of tier-2 commonality can be correlated with geographical or industry concentration of tier-1 suppliers. Meanwhile, tier-1 supplier concentration itself is likely to be correlated with tier-0 firm risk, which may in turn bias our estimates. Therefore, in this section, we test whether the effect of tier-2 supplier commonality can actually be explained away by tier-1 supplier geographical or industry-wise concentration.

We compute the tier-1 concentration using the Herfindahl index, $H = \sum_{i=1}^{N} p_i^2$, where N is the total number of countries of origins (sub-industries), and p_i represents the share of firms' tier-1 suppliers in the ith country (sub-industry). Intuitively, a smaller Herfindahl index indicates a less concentrated, or in other words, more diversified tier-1 supplier base. Results in columns (b) to (d) in Table 11 confirm that the measured impacts of the diamond ratio and cosine commonality score are robust after controlling for tier-1 geographic and industry concentration. The magnitude of the effects is also similar compared to that in the original analyses, which is provided in column (a) in the same table.

Table 11 Tier-1 supplier concentration

DEPENDENT VARIABLE: Log Volatility	(a) Tier-2 & Sub-tier supply network	(b) Geographic Concentration	(c) Sub-industry Concentration	(d) Both Concentrations
Panel A. Sub-tier supply network (diamond ratio)				
Diamond Ratio	0.384***	0.532***	0.357***	0.493***
	(0.126)	(0.136)	(0.139)	(0.147)
Geographic Concentration		-0.200***		-0.203***
		(0.073)		(0.073)
Sub-industry Concentration			0.045	0.058
			(0.071)	(0.071)
Panel B Sub-tier supply network (cosine commonality)				
Cosine Commonality	0.374***	0.399***	0.356**	0.384***
	(0.141)	(0.140)	(0.141)	(0.139)
Geographic Concentration		-0.088		-0.144**
		(0.063)		(0.067)
Sub-industry Concentration			0.094*	0.141**
			(0.057)	(0.060)
All Panels				
Observations	25,848	25,848	25,848	25,848
Number of Firms	2,277	2,277	2,277	2,277

Notes. Robust cluster-adjusted standard errors are shown in parenthesis. All the covariates are included with log transformation except for the network measures. To simplify the table, we do not report on market risk, tier-1 supply risk, financial and operational covariates, country, sector and missing controls. *** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.

6.3. Tier-2 Suppliers: Semiconductor vs. Non-Semiconductor Firms

In the previous analysis, we document that the most heavily shared tier-2 suppliers are semiconductor firms while most tier-0 firms whose supply network involves heavily shared tier-2 suppliers sell directly to consumers. We also find that there is a strong positive association between the risk of these heavily shared tier-2s and the risk of the associated tier-0 firms. One may suspect that the relationship we observe may simply come from the correlation between these two sub-industries. To test whether this is the case, we construct additional risk measures for semiconductor and non-semiconductor tier-2 suppliers, respectively.

Table 12 Tier-2 suppliers: semiconductor vs. non-semiconductor firms

DEPENDENT VARIABLE: Log Volatility	(a) Tier-2 shared by >=5 Tier-1s	(b) Semi-conductor Tier-2 shared by >=5 Tier-1s	(c) Other Tier-2 shared by >=5 Tier-1s	(d) Tier-2 shared by ≥ 5 Tier-1s (Separate)
Common Tier-2 Supplier Risk	0.197***			
	(0.048)			
Semi-conductor Common Tier-2 Supplier Risk		0.151***		0.099*
		(0.049)		(0.055)
Other CommonTier-2 Supplier Risk			0.158***	0.110*
			(0.051)	(0.057)
Market Risk	0.459***	0.460***	0.461***	0.460***
	(0.009)	(0.009)	(0.009)	(0.009)
Tier-1 Supplier Risk	0.056***	0.058***	0.058***	0.057***
	(0.013)	(0.013)	(0.013)	(0.013)
Financial and Operational controls	Yes	Yes	Yes	Yes
Missing controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Observations	25,848	25,848	25,848	25,848
Number of Firms	2,277	2,277	2,277	2,277
R-squared	0.7152	0.7150	0.7150	0.7150

Notes. Robust cluster-adjusted standard errors are shown in parenthesis. All the covariates are included with log transformation. The overall R-squared value is reported in all columns. To simplify the table, we do not report on controls. *** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.

Results in column (b) to (d) demonstrate that the effects are consistent across semiconductor tier-2 suppliers and non-semiconductor tier-2 suppliers. The risks of both types of suppliers, when heavily shared, have a strong positive association with tier-0 firm risk. The estimates are also consistent with the original estimates without distinguishing semiconductor tier-2 suppliers.

7. Conclusion

Our results provide the first empirical evidence on how the sub-tier network structure affects the total equity risk of a firm. We construct the supply network of the high-tech sector using a new global supplier dataset from Bloomberg. Compared to commonly used supplier-customer relationship databases, this database substantively expands the coverage of suppliers of both domestic and international suppliers. It gives us greater visibility into the multi-tiered supply network, and hence allows us to test the impact of sub-tier network structure on firm risk.

Based on the constructed supply network, we find that overlapping in tier-2 suppliers is prevalent in the high-tech sector. On average, 20 percent of tier-2 suppliers are shared by two or more tier-1 suppliers and 2.3 percent of tier-2 suppliers are shared by at least five tier-1 suppliers. Such a network feature has an important implication for risk aggregation in supply networks. We find a strong positive association between shared tier-2 supplier risk and tier-0 firm's risk. The association increases when tier-2 suppliers are shared by more tier-1 suppliers. We propose two network measures of tier-2 commonality, the diamond ratio and cosine commonality score, to isolate the impact of a risky supply network from risky suppliers. We find that one standard deviation increase in the diamond ratio (cosine commonality score) leads to 0.58 (0.41) standard deviation increase in the tier-0 firm's risk. Given that both tier-0 firm and tier-1 suppliers have very limited knowledge of tier-2 commonality and hence are unlikely to take actions in response, we are able to identify the causal effect of tier-2 commonality on tier-0 firm risk.

Our study highlights the need for firms to increase visibility into their sub-tier supply network because of substantial unseen and unmanaged supply chain risks they impose. In particular, firms should identify critical sub-tier suppliers that are shared by multiple immediate suppliers and proactively manage the associated risks. The metrics of sub-tier commonality proposed in this paper can also be applied to other industries to study the prevalence and impact of sub-tier commonality and to assess consequent risks.

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Appendix. Tables

Table A1 Coverage bias

DEPENDENT VARIABLE: 0/1 Indicator Probit Model	(a) No Supplier Reported (0)	(b) Less than Five Suppliers Reported (0)
Market Capitalization	0.052***	0.163***
	(0.003)	(0.004)
United States	-0.191***	0.011
	(0.030)	(0.031)
Japan	0.036	-0.184***
	(0.030)	(0.031)
Korea	-0.356***	-0.628***
	(0.033)	(0.042)
Mainland China	-0.263***	-0.593***
	(0.034)	(0.041)
Taiwan	0.402***	0.137***
	(0.031)	(0.031)
Household Durables (252010)	0.172***	0.293***
	(0.045)	(0.042)
Internet Software & Services (451010)	-0.242***	-0.374***
	(0.047)	(0.058)
IT Services (451020)	0.036	-0.223***
	(0.034)	(0.040)
Software (451030)	-0.315***	-0.484***
	(0.032)	(0.040)
Communications Equipment (452010)	0.116***	-0.080**
	(0.035)	(0.037)
Computers & Peripherals (452020)	0.327***	0.475***
	(0.040)	(0.033)
Electronic Equipment, Instruments & Components	0.032	0.146***
(452030)	(0.025)	(0.025)
Constant	0.682***	-1.589***
	(0.030)	(0.036)
Observations	28,260	28,260
R-squared	0.0433	0.1289

Notes. Robust standard errors are shown in parenthesis. Covariate market capitalization is included with log transformation. Pseudo R-squared value is reported in all columns. *** --- 0.01 level, **--- 0.05 level and *--- 0.1 level.