SOURCING DECISIONS IN THE PRESENCE OF HIGH IMPACT, LOW PROBABILITY SUPPLY CHAIN DISRUPTIONS

A Dissertation in
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by
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ABSTRACT

In this dissertation I investigate sourcing decisions in the presence of high impact, low probability supply chain disruptions. First, in Chapter 1, I present the motivation for my research and explain why the research questions that I pose are both important and timely.

In Chapter 2, I experimentally investigate how sourcing decisions are affected by experiencing a supply disruption and the lack thereof. I predict, and find evidence for, an oscillating pattern of sourcing, where the supply base is temporarily increased following the experience of a severe supply disruption, which is then followed by a gradual reduction of the supply base when there is no subsequent disruption. This oscillating sourcing pattern results in a tendency for decision makers to under-diversify their supply base. I propose an explanation of this behavior pattern to be the lack of reinforcement of the realized cost of a supply disruption and the lack of saliency of the expected cost of supply disruptions.

In Chapter 3, I expand upon this research and consider two options for diversification: supplier diversification (as presented in Chapter 2) and regional diversification. Specifically, I fix the cost of supplier diversification and vary the cost of regional diversification, resulting in three conditions, where theory predicts it is optimal to source from one region, source from either one or two regions (indifference), and source from two regions. The results indicate that decision makers tend to adopt and retain a sourcing strategy, utilizing suppliers that are perceived to be less risky. I also identify additional support for the tendency of decision makers to under-diversify their supply base in both the number of suppliers and regions.

Lastly, in Chapter 4, I summarize the results of the dissertation and discuss the implications for practitioners.
### TABLE OF CONTENTS

| LIST OF TABLES | vi |
| ACKNOWLEDGEMENTS | vii |
| Chapter 1  Introduction | 1 |
| Chapter 2  Supply Base Diversification in the Presence of High Impact, Low Probability Supply Disruptions | 3 |
| Chapter 3  Diversification as a Strategy for Managing Supply Chain Disruptions | 28 |
| Chapter 4  Conclusion and Future Research | 47 |
| References | 49 |
| Appendix A  Sample Instructions | 54 |
| Appendix B  Screenshots of the User Interface | 56 |
| Appendix C  Sample Instructions | 58 |
| Appendix D  Screenshots of the User Interface | 61 |
LIST OF FIGURES

Figure 2-1: Frequencies of Dual Sourcing. .................................................................20

Figure 3-1: Total Expected Cost of Sourcing Decisions. ............................................39
LIST OF TABLES

Table 2-1: Overview of Experimental Conditions (including sample size M). .......................16

Table 2-2: Estimation Results: Effects of Fixed Cost and Disruption Cost on Sourcing Decisions. .................................................................................................................................21

Table 2-3: Dual sourcing (in %), conditional on previous round’s choice (single, dual) and disruption (no, yes). .................................................................................................................23

Table 2-4: Estimation Results. ..............................................................................................................24

Table 3-1: Summary Statistics..................................................................................................................41

Table 3-2: Likelihood of Sourcing from Multiple Regions........................................................................42

Table 3-3: Estimation Results. ..................................................................................................................43

Table 3-3: Estimation Results. ..................................................................................................................44
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To my family
Chapter 1

Introduction

In recent years, supply chain initiatives to improve financial performance have driven increased operational effectiveness and efficiency within organizations. However, these initiatives have resulted in longer and more complex supply chains, increasing the risk of supply chain disruptions (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). While there are different strategies for managing supply disruptions (Tang, 2006), I specifically examine supplier diversification. Though supplier diversification allows for greater responsiveness to supply disruptions, it comes at the cost of decreased efficiency gains. In this dissertation, I study this critical tradeoff, examining sourcing decisions in the presence of a low probability risk of disruption.

In Chapter 2, I use behavioral experiments to answer the research question “How do low probability supply chain disruptions affect managerial sourcing decisions?” Specifically, I examine how the cost of supply diversification and the severity of a supply disruption affect sourcing decisions immediately following rarely occurring supply disruptions and in the intervening time without supply disruptions. Using a controlled laboratory experiment, I find evidence for an oscillating sourcing pattern, where decision makers temporally increase their supply base immediately after a severe disruption, followed by reductions during stretches without disruptions. In Chapter 3, I examine diversification strategies used in supply chains, evaluating sourcing strategies when both individual suppliers and groups of suppliers, based in a
specific regions, face the risk of disruptions. As in Chapter 2, I take a behavioral approach, establishing an experimental design in which it is always theoretically optimal to dual source, and where the theoretical optimal number of regions varies with the regional cost. The resulting three conditions, single region, dual region, and indifference, provide an answer the question, “How do decision makers prepare for and respond to supply chain disruptions, when multiple risks and safeguard strategies exist?” In theory, decision makers should dual source and vary the number of regions according to the cost of regional diversification, but I find that subjects consistently under-diversify their supply base.

Finally, in Chapter 4, I review the research contributions of this dissertation and discuss directions for future research.
Chapter 2

Supply Base Diversification in the Presence of High Impact, Low Probability Supply Disruptions

Abstract

This paper investigates decision making in the context of strategic sourcing in the presence of high impact, low probability supply disruptions. I develop a simple theoretical model that captures one of the central tradeoffs for strategic sourcing decisions – while a lean (diversified) supply base reduces (increases) transaction costs, it increases (reduces) the exposure to costly supply disruptions. Through the use of a controlled laboratory experiment, I predict and find evidence for an oscillating sourcing pattern - decision makers temporally increase their supply base immediately after a severe disruption, followed by reductions during stretches without disruptions. As I investigate decision making in a stable environment, this pattern constitutes a costly bias. Furthermore, I find that decision makers tend to under-diversify their supply base, which may be linked to the fact that low-probability disruptions evidently (almost) never happen. Thus, disruptions remain latent in the background of the decision problem, resulting in infrequent reinforcement of the (perceived) value of a diversified supply base.

Introduction

In February 1997, a fire erupted in Aisin’s Kariya plant, completely destroying the line dedicated to the production of P-valves, a brake component used on all Toyota vehicles (Nishiguchi & Beaudet, 1998). Aisin was the single supplier of this critical component, and because of JIT operations, only one day’s worth of supply was immediately available. A number
of Toyota and Aisin suppliers set up temporary manufacturing of P-valves, allowing Toyota to restore production three days later. Following this disruption, Toyota implemented a review process to ensure that all components were dual sourced. This lesson in supply base diversification was short-lived, though, as Toyota gradually rationalized their supply base again in the 2000s, gaining “unprecedented economies of scale by using single suppliers for entire ranges of its cars across multiple markets” (“Toyota’s overstretched supply chain: The machine that ran too hot,” 2010). Fourteen years after the Kariya incident, Toyota was again faced with supply disruptions following Japan’s Tohoku Earthquake and Tsunami in March 2011. A number of Toyota’s parts suppliers, which were mostly single sourced, faced supply disruptions lasting more than six months and cost Toyota more than $880 million. Toyota, again, re-evaluated its existing supply chain strategy, requiring its sole-source suppliers to either create redundancy of their production or hold extra inventory while also considering more dual-sourcing (Gilmore, 2012).

The above example illustrates a key trade-off many supply chains face with regard to their sourcing strategy. While supply base rationalization promises substantial efficiency gains (at the cost of responsiveness), supply base diversification allows for responsiveness, e.g., in the case of a disruption (however, at the cost of efficiency). More importantly, the example illustrates how sourcing strategies evolve dynamically over time: as Toyota seemingly tried to adapt to new circumstances, the company diversified its supply base in response to a costly disruption, followed by a gradual supply base rationalization during periods without any disruption. Such oscillating patterns appear sensible, as firms continuously monitor and adjust their sourcing strategies in order to adapt to changes in overall competitive strategy, market conditions, and various stakeholder expectations. Thus, Toyota’s gradual supply base rationalization in the 2000s may well reflect an increasing competitive pressure towards cost efficiency. Similarly, Toyota’s shift towards dual sourcing after the major supply disruptions in 1997 and 2011 may well reflect a
thorough re-assessment of the company’s exposure to supply disruptions. However, unless I am willing to assume that the relevant probabilities factually increased significantly with the occurrence of the disruption, Toyota’s adjustments immediately suggest that their sourcing strategy was mis-calibrated, either before or after the disruptions (or both), even though it is not clear whether their supply base was under-diversified before the disruptions or over-diversified afterwards (or both). For obvious reasons, the example has to be interpreted with caution, yet Toyota’s inter-temporal adjustments in their sourcing strategy leave a sense of a persistent and costly bias in their supply base decisions.

This study is an attempt to identify behavioral aspects that may underlie the oscillating diversification/rationalization pattern highlighted in the example above. The central premise is that decision bias arises because of the obvious probability of low-probability disruptions - they rarely happen, rendering difficult the accurate assessment of the relevant probabilities, expected costs and, hence, the expected value of a supply diversification strategy. When decision makers attempt to learn the value of a sourcing strategy by experiential sampling (rather than ex ante stochastic optimization), this gives rise to an oscillating pattern of supply base diversification after a severe disruption, followed by a gradual supply base rationalization during long periods of time without disruptions, followed by supply base diversification after another disruption, and so on. Moreover, as a supply base diversification strategy rarely receives positive reinforcement, whereas a supply base rationalization strategy frequently does, this oscillating pattern predicts under-diversification on average.¹

The clean identification of such behavioral patterns in a field setting like Toyota is difficult (arguably impossible) for a number of reasons. For example, while I question whether Toyota’s strategic oscillations were rational reactions to updated disruption probabilities, a

¹ Obviously, this prediction hinges on certain assumptions regarding the frequency and severity of disruption events.
rigorous test of this claim would require precise estimates of the structure and parameters of the stochastic process governing the (non)-occurrence of disruption (which I do not have). Similarly, investigating under- versus over-diversification is meaningful only in the presence of some normative benchmark (“optimal diversification”), which would require precise knowledge of Toyota’s cost structure and objective function (which I also do not have). As control over these factors is important for my purposes, my research questions were studied in a laboratory setting.

I first develop a simple theoretical model that captures the trade-off between supply base rationalization and diversification. In my model, a single firm needs to source a fixed number of parts from a set of two homogenous suppliers. Each supplier has a known probability of being disrupted, in which case the supplier cannot deliver any parts. On the one hand, the firm incurs a fixed cost for each supplier it sources from, providing there is an incentive to rationalize the supply base. On the other hand, the cost structure is such that a disruption is most costly under single sourcing, providing the incentive to diversify the supply base. My experimental design varies the cost of a disruption (high versus low) and the cost of diversification (high versus low). For the resulting four conditions, theory predicts single sourcing, dual sourcing, and indifference, which leaves sufficient room to detect over- and under-diversification (as well as optimal decision making). Importantly, my experimental implementation keeps the disruption probabilities identical and independent across periods. This provides a strong test for the hypothesized oscillating pattern, as there exists no (rational) reason to ever change the sourcing strategy.

Decision makers in my experiment tend to under-diversify their supply base on average, relative to the risk-neutral benchmark. This result is consistent with two opposing reinforcement patterns in my data, which resemble the oscillations highlighted in the Toyota example. In my experiments, I find that subjects temporarily increase their supply base after severe disruptions with a single-sourced supplier, followed by a gradual gravitation back towards single sourcing.
Taking into account that low-probability disruptions rarely happen, an *average* under-diversification may result when *infrequent* reinforcements of a dual sourcing strategy (after a severe disruption) are outweighed by the *frequent* reinforcements of a single sourcing strategy (after no disruption).

This paper proceeds as follows. In Section 2, I provide a brief overview of the literature. In Sections 3 and 4, I develop a simple theoretical model and my research hypotheses, respectively. Sections 5 and 6 present the results from a laboratory study designed to test these hypotheses. Finally, Section 7 summarizes my findings and provides managerial insights.

**Literature Review**

Supplier selection management plays a critical role in the ability of a supply chain to operate effectively and efficiently (Fearon, Dobler, & Killen, 1992). Indeed, Hendricks and Singhal (2003, 2005) empirically show that supply chain disruptions result in decreased operating performance, and these negative changes in performance linger long after the disruption event. There exists a large body of literature that examines a variety of sourcing strategies to manage different types of supply risk (e.g., reliability, cost, quality, etc.) (c.f., Elmaghraby, 2000). More recently, Tomlin and Wang (2011) and Aydin et al. (2011) review the broad literature on managing supply risk.

To mitigate the impact of supply uncertainty for a given supply base, firms can consider the potential random yield in determining the ideal order quantities (c.f., Yano & Lee, 1995). Another supply risk mitigation approach is to consider supply uncertainty during the supplier selection process. These approaches are of course not mutually exclusive as supplier selection and quantities can be determined simultaneously. As my focus here is on the supplier selection
decision, I concentrate my discussion on literature relating to supplier selection decisions in the presence of supply uncertainty rather than the broad, random yield literature.

Multiple-sourcing has been identified as an effective strategy in managing supply chain disruption risks (Kleindorfer & Saad, 2005; Sheffi, 2001; Tang, 2006; Mark Treleven & Schweikhart, 1988) by hedging against the risk of supplier failures (Sarkar et al., 2013), but there is also competing evidence of supply base consolidation (Monczka, Trent, & Callahan, 1993; Trent & Monczka, 1998), in an effort to reduce administrative and transaction costs (Choi & Krause, 2006). In consolidating its supply base, an organization becomes increasingly reliant on the remaining suppliers and thus increasingly vulnerable to disruptions that may have a severe negative impact on operations (Burke, Carrillo, & Vakharia, 2007; Nishiguchi & Beaudet, 1998). In addition to the potential cost savings associated with supply base consolidation, other factors will affect supplier selection. Zsidisin (2003) and Ellis et al. (2010) identify the probability and magnitude of supply disruptions as the factors most frequently identified by procurement managers as critical in managing supply risk.

Analytical studies of supplier selection have shown that in some instances it is advantageous to single source, and in other instances supplier diversification is preferable (Richardson & Roumasset, 1995; Sarkar et al., 2013). The optimality of single versus multiple sourcing will, of course, depend on the model assumptions. As noted above (Choi & Krause, 2006) single sourcing may result lower fixed costs, and the inclusion or exclusion of fixed cost, or some other version of economies of scale, will influence the optimal sourcing decision. Consider for example, the model of Dada et al. (2007) for a firm sourcing from a pool of suppliers varying in their (unit) cost and reliability. They find that when there is no fixed cost associated with using a supplier, the optimal sourcing decision is to multi-source, using the least expensive $k$ of $n$ suppliers no matter the unreliability of those suppliers. In this setting, an inexpensive but very unreliable supplier may be allocated a very small quantity, and the authors point out that a fixed
cost associated with such a supplier could result in their de-selection; thus, the presence of fixed costs could switch the optimal sourcing strategy from multiple to single sourcing. Ruiz-Torres and Mahmoodi (2007) examine optimal sourcing decisions when individual suppliers are at risk of failure. Their model includes a fixed cost or utilizing a supplier, and they find that when suppliers are highly reliable (low risk of failure) single sourcing is the lowest cost strategy, but as suppliers become less reliable (higher risk of failure) supplier diversification becomes a more effective strategy.

Multi-sourcing may still be optimal even if supplier fixed costs are not present. Examining sourcing decisions from two suppliers, one reliable one not, Tomlin (2006) provides some insight into sourcing strategies, finding that characteristics of the disruption affect the optimal sourcing strategy of which supplier(s) to source from, with more frequent or longer disruptions driving sourcing from the less reliable to the more reliable supplier. Buyer risk preferences and potential volume flexibility from the reliable supplier can also affect the optimal sourcing strategy.

In contrast to the above papers where full information is assumed, several papers examine sourcing decisions when the buyer has imperfect information about suppliers’ costs, reliability or both. Chaturvedi & Martinez-de-Albeniz (2011) investigate optimal supplier selection mechanisms when the buyer may have only partial information regarding the costs and reliabilities of the potential suppliers. Yang et al. (2012) also examine the case where the buyer does not have full information regarding the supplier’s reliability but focus on the impact of competition on the buyer’s preference (or lack) for supply diversification. Gümüş et al. (2012) study how a supplier facing competition may be able to convey information about their reliability. Tomlin (2009) studies a setting where ongoing transactions allow the buyer to update his understanding of the suppliers’ reliability.
As I investigate the supply base diversification decision through a behavioral lens, my study is related to a swiftly growing literature in Behavioral Operations Management research. While there are a growing number of studies on decision making under demand risk, often in the context of the classic newsvendor model (Bolton & Katok, 2008; Kremer, Moritz, & Siemsen, 2011; Schweitzer & Cachon, 2000), research regarding supply risk remains limited. Importantly, the vast majority of Behavioral Operations studies address recurrent risk where the outcomes of the risky variable (i.e., demands) resolve themselves on a regular basis, which is fundamentally different from the low-probability all-or-nothing type of risk of supply disruptions.

Perhaps most similar to my work is Gurnani et al. (2013), who experimentally examine decision making in a setting with two suppliers, one reliable and one unreliable but less costly. In their model, the marginal cost of missing a sale is constant and equal to the lost margin. As a result, it is always optimal to single source, using the reliable supplier exclusively if the per-unit cost premium is low and/or the unreliable supplier’s disruption risk is high. In contrast to this normative benchmark, they find that subjects tend to dual source, in a sense consistently over-diversifying their supply base. While I also seek to identify systematic tendencies of procurement managers in supplier selection decisions, my study differs from Gurnani et al. (2013) in important ways. In contrast to Gurnani et al. (2013), I test the impact of the frequent reinforcement of supplier fixed cost relative to the infrequent reinforcement of disruption. My model features symmetric supplies, each with a fixed cost, as well as marginally increasing cost of missed demand (c.f., Tsay & Agrawal, 2000). This model allows me to test both under- and over-diversification.
Theoretical Model

I develop a theoretical model that provides a benchmark for my experimental studies. There exist two potentially complementary strategies for managing supply chain disruption risks: supplier diversification and investment in excess inventory. To focus on the supplier diversification decision, I fix the total quantity ordered to be equal to the deterministic demand \( D \). In each round the decision maker equally allocates the total order quantity among \( n \) of the \( N \) homogenous suppliers, where each supplier faces an independent and identical probability of a disruption \( p \). If a supplier is disrupted, they deliver no units to the buyer.

The procurement manager’s objective is to minimize expected cost by deciding the number of suppliers \( n \) from which to procure, balancing the fixed cost \( \delta \) of each supplier with the cost of a supply disruption, which is marginally increasing with each unit not delivered (c.f., Tsay & Agrawal, 2000). For example, an organization that faces a small number of units short might fail to satisfy the demand of transactional or spot market customers, losing the margin but not necessarily losing future business. The same firm with a larger demand shortfall might disappoint valuable customers, incurring penalties for failing to meet service level agreements or potentially losing a future stream of business. I model this marginally increasing cost of failed deliveries with a quadratic cost function that captures all consequences of failed deliveries including potential lost margin and any other goodwill costs, \( \sigma(n) = \alpha(Dk(n)/n)^2 \), where \( k(n) \) is the number of failed deliveries.

The procurement manager can reduce the fixed cost of supply diversification by decreasing the supply base, which would in turn increase the severity of a supply disruption, or vice versa. The manager’s total expected cost function is given by:

\[
C(n) = \delta n + E[\sigma(n)]
\]
where \( \delta n \) is the total fixed cost of sourcing from \( n \) suppliers and \( \mathbb{E}[\sigma(n)] \) is the expected disruption cost. Given the quadratic disruption cost function and using the fact that \( k(n) \) is binomially distributed\(^2\), I can rewrite the expected cost function as:

\[
C(n) = \delta n + \frac{\alpha D^2}{n^2} \left[ (np(1-p) + n^2(1-p)^2 \right]
\]

Relaxing the integrality requirement\(^3\) for \( n \), I derive the following expression for the optimal number of suppliers:

\[
n^* = D \sqrt{\frac{\alpha p (1-p)}{\delta}}.
\]

From equation (1) I observe that the optimal number of suppliers is dependent on demand, the probability of disruption, the disruption cost, and the fixed cost. In my experiments, I fix demand and the probability of disruption. In doing so, I am able to examine how changes in \( \delta \), the fixed cost, and \( \alpha \), the constant in the quadratic disruption cost function affect subject sourcing decisions.

**Hypotheses**

Rational behavior assumes that when decision makers are provided full knowledge of the structure of the game, they have the ability to go through the reasoning process and correctly determine the appropriate (optimal) decision. Classical studies (e.g., Kahneman & Tversky, 1979) testing the rationality assumption have found that decisions often deviate from rational choice, with decision makers exhibiting oversensitivity to rare events (Kahneman & Tversky, 1979). In contrast to such “decisions from description” are studies of “decisions from experience” (Hertwig, Barron, Weber, & Erev, 2004), where decision makers have no prior knowledge of the

\(^2\) With each of \( n \) suppliers having independent probability of successful delivery \( 1 - p \), \( k(n) \) is binomially distributed, so \( \mathbb{E}[k(n)^2] = np(1-p) + n^2(1-p)^2 \).

\(^3\) For any particular setting, one must check the integers nearest \( n^* \) to find the optimal decision.
structure of the game and must solely rely on past experience. When relying on experience only, decision makers exhibit under-sensitivity to rare events.

In this paper I investigate decision making with full information over repeated trials. The decision maker, who is provided full knowledge of the structure of the game, makes repeated sourcing decisions, with each round of the experiment consisting of a sourcing decision, followed by feedback on the outcome of each decision after each round. Subjects are provided full information of the game, but the fixed cost of supply diversification is easily calculated: with certainty, the fixed cost of sourcing from \( n \) suppliers is \( \delta n \); whereas the expected disruption cost is more difficult to calculate: when single sourcing there is a 1\% probability that the disruption cost is \( \alpha D^2 \) and a 99\% probability that the disruption cost is 0; when dual sourcing there is approximately a 2\% probability that the disruption cost is \( \alpha (D)^2 / 4 \) and approximately a 98\% probability that the disruption cost is 0. Furthermore, subjects are aware that they are playing repeated trials, where disruptions are independent and identically distributed across rounds. This “description-experience” setting differs from models based purely on experience or description, and therefore, I do not expect to observe the same biases.

In my setting, I hypothesize that subjects exhibit biases resulting from both the lack of salience (Description) and the lack of reinforcement (Experience) of supply disruptions. First, I expect that the regularly occurring fixed cost of diversification is easily comprehended, but that subjects are insufficiently sensitive to rare and extreme outcomes (Barron & Erev, 2003), with decisions based on the assumption that low probability events “won’t happen to me.” Second, prior success may lead decision makers to refine existing approaches, but not to challenge them (Lant, 1992). Because investing in supplier diversification involves an upfront cost to achieve a delayed, and rarely encountered benefit, reducing the supply base will rarely be penalized and diversifying the supply base rarely compensated. This lack of reinforcement is further exacerbated by the fact that a reduction in the supply base reduces the probability of a subject
experiencing a supply disruption, which reduces the frequency of supply disruptions, which, in turn, could lead to further reductions in the supply base.

It is only when confronted with a supply disruption that decision makers question their previous sourcing decision. Meyer (2012) investigates decisions over time regarding investment in hurricane mitigation, finding that in the absence of losses, decision makers reduce investments in protection (insurance), and only the experience of a loss will increase investment in this protection. I hypothesize that sourcing decisions are affected, not only by the experience of a supply disruption, but also by the magnitude of that supply disruption.

**Hypothesis 1 (No Disruption).** Without experiencing a supply disruption, decision makers reduce their supply base in accordance with the magnitude of the supply cost.

**Hypothesis 2 (Disruption).** Following a supply disruption, decision makers increase their supply base in accordance with the magnitude of the disruption cost.

I posit that decision makers understand the basic dynamics of supply and disruption costs, increasing (decreasing) the supply base as the marginal cost of adding suppliers decreases (increases). Similarly, decision makers will source from more suppliers as the disruption cost increases. I hypothesize that sourcing decisions are more sensitive to changes in supplier fixed cost than to changes in the disruption cost, based on the lack of salience and lack of reinforcement of supply disruptions relative to fixed supply costs.

**Hypothesis 3 (Sensitivity).** Decision makers are more sensitive to the fixed cost of diversification than to cost of supply disruptions.

Finally, the frequent reinforcement on the cost of diversification combined with infrequent reinforcement of the consequences of disruption would result in a greater incidence of
supply base reduction compared to supply base diversification. Taken on average, this results in the propensity for subjects to under-diversify the supply base.

**HYPOTHESIS 4 (UNDER-DIVERSIFICATION).** Decision makers under-diversify on average.

**Experimental Design and Implementation**

To test my research hypotheses, I design experiments in which subjects make repeated sourcing decisions. In particular, in each of the 200 rounds of the experiment, subjects must choose the number of suppliers \( n \) from a set of \( N = 2 \) homogenous suppliers to meet demand, \( D \). In each round, I fix demand to 100 units and allocate the order equally across suppliers. Each supplier is disrupted with probability \( p = 0.01 \), which is independent and identically distributed across suppliers and rounds. If disrupted, a supplier would not deliver any of the \( \left( \frac{D}{n} \right) \) units.

**Design**

My experimental design, summarized in Table 2-1, includes two between-subject treatment variables, each on two levels: the fixed cost of sourcing from a supplier, \( \delta \in \{50, 10\} \), and the constant \( \alpha \) in the expected disruption cost function, \( \alpha \in \{1.01, 0.20\} \). The parameter values were chosen in order to create a balanced design which includes one condition with \( n^* = 1 \), one condition with \( n^* = 2 \), and two conditions for which a rational risk-neutral decision maker would be indifferent between single and dual sourcing. I label the resulting four conditions intuitively as S(ingle Sourcing), D(ual Sourcing), I(ndifferent with high \( \delta \), \( \alpha \)), and I(ndifferent
with low $\delta, \alpha$). My design is balanced in the sense that it leaves sufficient room for both under and over-diversification, and thus is a fair testing environment for Hypothesis 4 (Under-diversification). Furthermore, the design allows for a direct test of Hypothesis 3 (Sensitivity), which posits that sourcing decisions are more sensitive to changes in the fixed cost, relative to changes in the disruption cost. In particular, letting $\bar{n}_c$ denote the observed average number of suppliers in condition $c \in \{S, I, I, D\}$, Hypothesis 1 predicts that $(\bar{n}_I - \bar{n}_S > \bar{n}_I - \bar{n}_S)$, and $(\bar{n}_I - \bar{n}_D < \bar{n}_I - \bar{n}_D)$.\(^4\)

Table 2-I: Overview of Experimental Conditions (including sample size $M$).

<table>
<thead>
<tr>
<th>Disruption Cost</th>
<th>$\alpha = 0.20$</th>
<th>$\alpha = 1.01$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Cost</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta = 50$</td>
<td>Condition $S$</td>
<td>Condition $I$</td>
</tr>
<tr>
<td>$n^* = 1$</td>
<td>$(M = 25)$</td>
<td>$n^* = 1 = 2$</td>
</tr>
<tr>
<td>$\delta = 10$</td>
<td>Condition $I$</td>
<td>Condition $D$</td>
</tr>
<tr>
<td>$n^* = 1 = 2$</td>
<td>$(M = 23)$</td>
<td>$n^* = 2$</td>
</tr>
<tr>
<td>$(M = 23)$</td>
<td>$(M = 28)$</td>
<td></td>
</tr>
</tbody>
</table>

**Task and Software**

The experiment was implemented in the experimental software zTree (Fischbacher, 2007). During each round, the subject’s decision was to choose how many suppliers, $n$, to source from. To do so, the subject could add a supplier to the supply base by clicking on a supplier icon, and could also remove a supplier from the supply base by clicking again on that supplier icon (screenshots of the user interface are provided in Appendix B).

\(^4\) These predictions assume $\bar{n}_D > \bar{n}_I > \bar{n}_S$. 
Screenshots of the User Interface).

**Information and Feedback**

After the subject confirmed her choice, the computer would simulate and visually represent the random outcomes (disruption or not), and subjects were provided with the total realized fixed cost and the total realized disruption cost data for that round. Importantly, I provided disruption information on both suppliers, regardless of the subject’s choice, i.e., I would include counterfactual information on suppliers that were not chosen. Even though I provide subjects with full knowledge about the relevant structure and parameters of their task environment, remember that I expect subjects to learn about the two options (single source or dual source) by experiential sampling over time. The inclusion of counterfactual information on disruptions of suppliers not chosen (under single sourcing) removes any incentive to dual source simply for reasons of information acquisition and learning (about disruption probabilities). Providing unconditional disruption information allows me to test whether observing a supply disruption (resulting in no disruption cost to the subject) affects sourcing decisions, and furthermore has ecological validity, as major supply disruptions in practice rarely go unnoticed by the sourcing firm’s competitors.

Finally, in each of the 200 rounds, subjects had access to a full history of delivery, cost and profit data from previous rounds.
Recruitment and Payment

The experiments were conducted in the behavioral laboratory at a large public university. Subjects were recruited from a subject pool associated with the behavioral laboratory. Prior to the experiment, subjects were provided with an instruction sheet, explaining the task and including formulas and illustrative examples of the fixed cost and realized cost of a supply disruption (Appendix A). In each of the 200 rounds, subjects incur either a fixed cost, or both a fixed cost and a disruption cost, thus subjects begin the experiment with an endowment and were tasked to minimize their total costs across the 200 rounds. The endowment was set at a sufficiently large level to prevent subjects from experiencing bankruptcy (Friedman & Sunder, 1994), and was determined by calculating the maximum total cost that could be incurred in each experimental condition, given the same underlying random draws of supply disruptions. Subject compensation was calculated as the endowment minus the total accrued costs of the subject across the 200 rounds of the experiment and then converted from laboratory dollars to USD for payment. The endowment and conversion rate were adjusted across the experimental conditions to ensure commensurate earnings. The average subject payment in the experiment was $16, with a maximum subject payment of $20 and a minimum subject payment of $8.

Results

My theory is pitched in terms of number of suppliers, \( n \), and the empirical meaning of my hypotheses is in terms of average number of suppliers, \( \bar{n} \). Given the binary nature of my data, my unit of analysis, and for convenience, I present my results in terms of frequencies, \( f_n = m_n / M \), where \( m_n \) is the total number of observations for \( n \) suppliers, and \( M \) is the total number of
observations. In particular, the following analysis will mostly be presented in terms of the frequency of dual sourcing, \( f_2 \), which has a one-to-one mapping with the average number of suppliers \( f_2 = \bar{n} - 1 \).

Figure 2-1 presents the results by condition. I first test observed choices against the theoretical predictions from Equation (1), using each subject’s frequency of dual sourcing, \( f_2 \), as the unit of analysis. For conditions \( \text{I} \) and \( \text{L} \), theory predicts indifference between single and dual sourcing, such that the fair test proportion is \( x = 50\% \). I find the empirical proportion to be significantly lower than 50\%, both for condition \( \text{I} \) (20\%, two-sided proportion test \( p<0.01 \)) and \( \text{L} \) (16\%, \( p<0.01 \)). For condition \( \text{S} \), I observe a small difference between observed and predicted proportions (2\% versus 0\%), while for condition \( \text{D} \), subjects dual source significantly less than they should (27\% versus 100\%). As the extreme test proportions of these two conditions do not allow for a direct statistical test without making unwarranted distributional assumptions, I instead use the following procedure. For condition \( \text{S} \) (\( \text{D} \)), I calculate the smallest (largest) test proportion \( x \) for which, I fail to reject the null hypothesis that the empirical proportion \( f_2 \) equals \( x \), i.e., \( H_0 : f_2 = x \). At confidence level of 95\%, I fail to reject this hypothesis for condition \( \text{S} \) at \( x = 1\% \). For condition \( \text{D} \), this critical test proportion is \( x = 42\% \).

Overall, these results suggest that decision makers tend to under-diversify their supply base on average. This is consistent with Hypothesis 4 (Under-diversification), which was in part based on the argument that the infrequent reinforcement of a dual sourcing strategy (after a severe disruption) is outweighed by the frequent reinforcement of a single sourcing strategy (after no disruption). As a simple test of this argument, I next examine whether the above comparisons hold when I constrain the analysis to the data from round 1 (included in the left columns in Figure 2-1), as these decisions are not affected by any kind of reinforcement by definition. A series of tests show that the data in round 1 behave similarly to the data from all rounds in terms of
comparison to normative benchmarks, for conditions $\overline{I}$ (30% versus 50%, $p=0.03$) and $I$ (26% versus 50%, $p=0.02$). Following the procedure explained above, I find a critical test proportion $x = 4\%$ for conditions $S$ (12%), and $x = 61\%$ for condition $D$ (43%). Importantly, I compare the proportion of dual sourcing during the first round with the proportion of dual sourcing during the remaining rounds ($t=2-200$). I find that the tendency to dual source is consistently higher in round one (i.e., before any reinforcements), for conditions $S$ (12% versus 2%, paired binomial test, $p<0.01$), $D$ (43% versus 27%, $p=0.05$), $\overline{I}$ (30% versus 20%, $p=0.07$), and $I$ (26% versus 16%, $p=0.39$). These results are consistent with the idea that subjects’ reactions to a disruption and, importantly, their response in rounds without disruptions, contribute to a supply base underdiversification on average.

Figure 2-1: Frequencies of Dual Sourcing.
I next analyze the sensitivity of average sourcing decisions to changes in the two key parameters in my experimental design. I first note that average sourcing decision across experimental conditions are consistent with the intuitive comparative static results encapsulated in Equation (1) – the propensity to dual source increases as supplier fixed costs decrease (S → I, and I → D), and as the disruption costs increase (S → I, and I → D). In line with Hypothesis 3 (Sensitivity), behavior is more sensitive to changes in fixed cost (20%-2%=18% for S → I, and 27%-16%=11% for I → D) than to changes in disruption costs (14% for S → I, and 7% for I → D), but the effect appears to be weak. To formally test these observations, I estimate a logistic regression model,

$$\Pr(n_t = 2) = \Phi[\beta_0 + \beta_1 I_{FC} + \beta_2 I_{PC} + \beta_3 I_{FC}I_{PC}].$$

(2)

where $I_{FC}$ is an indicator variable for fixed cost (e.g., $I_{FC} = 1$ for low fixed cost, $\delta = \$10$) and $I_{PC}$ is an indicator variable for disruption cost (e.g., $I_{PC} = 1$ for high disruption cost, $\alpha = \$1.01$). The results are presented in Table 2-2. As expected, and using the data from all rounds, the probability to dual source decreases in the fixed cost ($\beta_1 = 2.46$, p<0.01) and increases in the disruption cost ($\beta_2 = 2.18$, p<0.01). Furthermore, and consistent with Hypothesis 3 (Sensitivity), these estimates suggest that fixed cost affect sourcing decisions more strongly than disruption cost ($\chi^2 (1) = 31.90$, p<0.01).

Table 2-2: Estimation Results: Effects of Fixed Cost and Disruption Cost on Sourcing Decisions.

<table>
<thead>
<tr>
<th>Variable</th>
<th>First round</th>
<th>All rounds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant ($\beta_0$)</td>
<td>-1.99**</td>
<td>-1.84**</td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td>(0.46)</td>
</tr>
<tr>
<td>Low Fixed Cost ($\beta_1$)</td>
<td>0.95</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td>(0.44)</td>
</tr>
<tr>
<td>High Disruption Cost ($\beta_2$)</td>
<td>1.14**</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>Interaction ($\beta_3$)</td>
<td>-0.39</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.95)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>LL</td>
<td>-119.64</td>
<td>-119.81</td>
</tr>
<tr>
<td>N</td>
<td>106</td>
<td>106</td>
</tr>
</tbody>
</table>
I observed a general tendency towards under-diversification, which is consistent with the reaction patterns predicted in Hypothesis 2 (Disruption) and Hypothesis 1 (No Disruption). To better understand how disruptions (or their non-occurrence) affect sourcing decisions, Table 2-3 shows choices conditional on the previous round’s choice (single source or dual source) and disruption event (no or yes).

I first turn to Hypothesis 2 (Disruption), which posits that decision makers increase their supply base as a response to a disruption, and that this effect is more pronounced the more severe the disruption (measured in terms of disruption cost). When subjects experienced a disruption with a single sourced supplier (the most costly disruption), I generally observe an increase in the probability to dual source in the subsequent round, in conditions S (8% versus 3%, Binomial test with subject-level proportion as the unit of analysis, p=0.02, I (17% versus 7%, p<0.01), l (6% versus 3%, p=0.10), and D (14% versus 4%, p<0.01). For the case of a disruption with a dual sourced strategy (the less costly disruption), Hypothesis 2 predicts a less pronounced, but positive effect. Interestingly, I observe a shift towards single sourcing, measured by a decrease in the probability of dual sourcing in the high fixed cost conditions, I (90% versus 79%, p=0.04), and D (87% versus 75%, p=0.05).

I next turn to Hypothesis 1 (No Disruption), which posits that decision makers would gradually gravitate towards single sourcing during long stretches of rounds without disruptions. To test this hypothesis formally on the level of data aggregation of, I compare (a) the probability of switching from single to dual sourcing with (b) the probability of switching from dual sourcing to single sourcing, for the cases when subjects experienced no disruption. For example, for condition S, subjects are less likely to switch from single to dual sourcing (3%), than to switch from dual to single sourcing (100%-47%=53%), and the difference is statistically significant.
I observe a similar pattern in conditions $\Pi$ (7% versus 31%, $p<0.01$), $I$ (3% versus 10%, $p<0.01$), and $D$ (4% versus 13%, $p<0.01$). Because they predominantly encounter rounds with no supply disruption, subjects are likely to gradually reduce their supply base over time. Together, these results support Hypothesis 1.

Table 2-3: Dual sourcing (in %), conditional on previous round’s choice (single, dual) and disruption (no, yes).

<table>
<thead>
<tr>
<th></th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single</td>
<td>3%</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td>7%</td>
<td>17%</td>
</tr>
<tr>
<td>Dual</td>
<td>47%</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>69%</td>
<td>54%</td>
</tr>
<tr>
<td>$S$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Pi$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$I$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In order to formally test the observed patterns in a single econometric framework, and shed further light on the strengths of the main effects, I next fit a logistic regression,

$$
\Pr(n_{i,t} = 2) = \Phi[\beta_S + \beta_D D_{t,t-1} + \beta_E E_{i,t-1} + \beta_{DE} D_{i,t-1} E_{i,t-1} + \beta_O O_{i,t-1} + \beta_t * t] \quad (3)
$$

where $D_{i,t-1}$ is an indicator variable for subject $i$ dual sourcing in round $t-1$, and $E_{i,t-1}$ is an indicator variable for subject $i$ experiencing a supply disruption in round $t-1$, and $E_{i,t-1} D_{i,t-1}$ is the corresponding interaction effect. Furthermore, I include round $t$ capturing any learning effects, noting the subtle difference between a linear decrease and the hypothesized supply base reduction when no disruption occurred. Finally, I include in my model an indicator variable ($O_{i,t-1}$) for subject $i$ observing (but not experiencing) a supply disruption in round $t-1$. $O_{i,t-1}$ is zero if the subject dual sourced in round $t-1$, since any disruption in this case must be experienced. The inclusion of $O_{i,t-1}$ allows for the test of a subtle distinction regarding the mechanism through which disruptions affect sourcing strategies. If decision makers used disruption events simply to update their subjective beliefs about the probability of future
disruptions, then it would not matter whether a disruption is experienced or only observed. If, on the other hand, disruptions matter only when they are experienced (hence, costly), then \( O_{t,t-1} \) would have no effect.

I estimate Equation (3) separately for each of the four conditions in my experimental design. I also estimate the model on the pooled data from all four conditions, for which I add indicator variables for the two main effects in my design, fixed cost \( (\delta) = 1 \) for low fixed cost, \( \delta = \$10 \) and disruption cost \( (\delta PC) = 1 \) for high disruption cost). Table 2-4 presents the results.

**Table 2-4: Estimation Results.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Condition S</th>
<th>Condition I</th>
<th>Condition D</th>
<th>Pooled Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>( \beta_S )</td>
<td>( \beta_I )</td>
<td>( \beta_D )</td>
<td>( \beta_D )</td>
</tr>
<tr>
<td></td>
<td>-3.62**</td>
<td>-2.60**</td>
<td>-3.65**</td>
<td>-3.12**</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.30)</td>
<td>(0.34)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Dual Sourced</td>
<td>( \beta_D )</td>
<td>( \beta_D )</td>
<td>( \beta_D )</td>
<td>( \beta_D )</td>
</tr>
<tr>
<td></td>
<td>3.51**</td>
<td>3.40**</td>
<td>5.90**</td>
<td>5.04**</td>
</tr>
<tr>
<td></td>
<td>(1.07)</td>
<td>(0.62)</td>
<td>(0.56)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Experienced a Supply Disruption</td>
<td>( \beta_E )</td>
<td>( \beta_E )</td>
<td>( \beta_E )</td>
<td>( \beta_E )</td>
</tr>
<tr>
<td></td>
<td>1.24</td>
<td>1.02**</td>
<td>0.89</td>
<td>1.27*</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
<td>(0.38)</td>
<td>(0.82)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>Dual Sourced and Experienced a Disruption</td>
<td>( \beta_{DE} )</td>
<td>( \beta_{DE} )</td>
<td>( \beta_{DE} )</td>
<td>( \beta_{DE} )</td>
</tr>
<tr>
<td></td>
<td>-1.11</td>
<td>-1.64</td>
<td>-1.81*</td>
<td>-2.09**</td>
</tr>
<tr>
<td></td>
<td>(1.44)</td>
<td>(0.46)</td>
<td>(0.88)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>Observed a Supply Disruption</td>
<td>( \beta_O )</td>
<td>( \beta_O )</td>
<td>( \beta_O )</td>
<td>( \beta_O )</td>
</tr>
<tr>
<td></td>
<td>0.38</td>
<td>-0.63</td>
<td>0.86</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.80)</td>
<td>(0.61)</td>
<td>(1.03)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>Round</td>
<td>( \beta_R )</td>
<td>( \beta_R )</td>
<td>( \beta_R )</td>
<td>( \beta_R )</td>
</tr>
<tr>
<td></td>
<td>-0.0075</td>
<td>-0.0010</td>
<td>0.0002</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0040)</td>
<td>(0.0012)</td>
<td>(0.0001)</td>
<td>(0.0009)</td>
</tr>
<tr>
<td>Low Fixed Cost</td>
<td>( \beta_{PC} )</td>
<td>( \beta_{PC} )</td>
<td>( \beta_{PC} )</td>
<td>( \beta_{PC} )</td>
</tr>
<tr>
<td></td>
<td>0.69**</td>
<td>0</td>
<td>0.0009</td>
<td>0.00006</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.25)</td>
<td>(0.26)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>High Disruption Cost</td>
<td>( \beta_{DC} )</td>
<td>( \beta_{DC} )</td>
<td>( \beta_{DC} )</td>
<td>( \beta_{DC} )</td>
</tr>
<tr>
<td></td>
<td>0.55*</td>
<td></td>
<td>0.55</td>
<td>(0.25)</td>
</tr>
</tbody>
</table>

Notes. Robust standard errors are in parentheses. **p≤0.01, *p≤0.05

For brevity, I focus most of the following discussion on the results from the pooled data (column 5 in the table). The estimation confirms most of my observations from Table 2-3. I find strong evidence for repeat choices – for example, after a round without a disruption, most subjects who had single-sourced (dual-sourced), will do so again, \( \beta_S < 0 \) (\( \beta_S + \beta_D > 0 \)). When they experience a disruption with a single sourced supplier, subjects are more likely to change their strategy to dual sourcing (\( \beta_E > 0 \)). Providing further evidence for the prediction that the disruption effect (Hypothesis 2) is moderated by the cost of a disruption, this result holds only for
the high disruption costs conditions \( \tilde{I} (\beta_E = 1.02, p = 0.01) \) and \( \tilde{D} (\beta_E = 1.27, p = 0.02) \). When they experience a disruption with a dual sourced supply base, subjects are more likely to change their strategy to single sourcing \((\beta_E + \beta_{DE} < 0, \text{except for condition } S)\), but this effect is only significant for the high fixed cost conditions, \( I \) and \( D \), and the pooled data. Overall, I interpret these results as partial support for Hypothesis 2 (Disruption) – subjects are likely to increase their supply base following severe supply disruption.

Regarding Hypothesis 1 (No Disruption), the relevant test is provided by a comparison of the relative magnitude of \( \beta_S \) (repeat single source) and \( \beta_S + \beta_D \) (repeat dual source). I find that over rounds without a disruption event, subjects that dual sourced are more likely to reduce their supply base than subjects that single sourced are likely to increase their supply base. Taken together, these effects result in a gradual supply base reduction over time without the reinforcement of a supply disruption, in line with Hypothesis 1.

Two additional results deserve mentioning. First, I do not observe any trends over time, as \( \beta_t \) is generally not significant. Second, my estimations do not pick up an effect of non-experienced disruptions (through \( \beta_0 \)). Under single sourcing, if the other (i.e., non-chosen) supplier is disrupted, this does not translate into a change of sourcing strategy.

**Conclusion**

In this study, I study how decision makers balance the tradeoff between supply base rationalization and diversification when facing low-probability, high-impact supply disruptions. Using controlled laboratory experiments, I study how the fixed cost of supply diversification and the cost of a supply disruption affect sourcing decisions. Additionally, I analyze how subject sourcing decisions change with no reinforcement of supply disruptions and immediately
following a supply disruption. From my experimental results I find evidence of three significant effects: (1) without experiencing a supply disruption, decision makers reduce their supply base; (2) decision makers are likely to increase their supply base following severe supply disruptions and likely to decrease their supply base following low-cost supply disruptions and when diversification is costly; and (3) decision makers are more sensitive to the cost of supplier diversification than to the expected cost of a supply disruption. These effects, when combined with the infrequent reinforcement of diversification leads decision makers to under-diversify on average.

Under-diversification is statistically and economically significant – for example, while subjects predominantly single sourced and left little money on the table in condition S, the tendency to under-diversify the supply base in condition D increased expected cost by 42%.

These effects lead me to suggest that subjects do not process information in a manner that is assumed by the theoretical model, but instead update their decisions based on lack of reinforcement of the realized cost of supply disruptions and the lack of saliency of the expected cost of supply disruptions. The behavior observed in the laboratory experiments complements anecdotal evidence that over time, without the reinforcement of a severe supply disruption, organizations are likely to reduce their investment in diversification strategies that can avert or limit the impact of a supply disruption. It is only following a severe supply disruption, that there is likely to be an immediate increase in the supply base. This oscillating pattern of investment in supply diversification provides a possible explanation why Toyota adopted diversification strategies following severe supply disruptions, only to fall back on single sourcing strategies.

Assuming that reinforcement and saliency are characteristics of decision making in practice under conditions of uncertainty, what can be done? The most important implication of

5 I note that, for the two indifference conditions, subjects were (unknowingly, unless they did the math) in the convenient position of achieving maximum expected profit regardless of their choices.
my research is that only when experiencing a severe supply disruption would decision makers diversify their supply chain. Therefore, the value of supply diversification is often neglected by sourcing managers and only considered following a severe supply chain disruption, but is likely to be neglected as time passes when no supply disruption occurs.

Given the low-probability of severe supply disruptions, breaking the cycle of reinforcement based decision making, which can lead to oscillating levels of supplier diversification, is not easy but it can be done. Organizations must first address the pervasive ‘cost-savings mentality’ that impacts their sourcing decisions. It is not enough for supply chain managers to identify and assess supply chain risks; they must also have in place proactive plans for such risks. In other words, supply chain managers must be appropriately incentivized to invest in supply chain diversification strategies in order to mitigate supply chain risks.
Chapter 3

Diversification as a Strategy for Managing Supply Chain Disruptions

Abstract

The trend towards lean supply chains and just-in-time manufacturing has reinforced the clustering of industries around specific geographic regions. While there are many advantages to clustering (Porter, 1998), there are also disadvantages: a regional supply disruption exposes the risk of concentrating supply chains. Thus, it is important for managers to recognize the tradeoffs between the efficiency and the risk of supply chain clustering. In an experimental setting, I investigate procurement decisions when two levels of supply uncertainty are present: (1) each supplier is at risk for unique supply disruptions and (2) each cluster of suppliers is at risk for a regional disruption. I find evidence of under diversification at both the supplier and regional levels.

Introduction

The competitive advantage of integrating supply chains has supported the growth of industry clusters: ‘geographically proximate groups of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities’ (Porter, 1998). There are a number of advantages to clusters, but in particular are the productivity gains that arise from vertical and horizontal integration centralized to a geographic region. Although these operational gains have allowed an overall reduction in costs, the concentration of an industry to a specific region has increased the risk that a regional disruption event can impact an entire
industry. This was the case of the hard disk drive (HDD) industry, which manufactures about 25 percent of the world’s HDDs in Thailand (Zhang, 2011a). In 2011, monsoon rains brought the worst flooding Thailand had seen in over 50 years, affecting the production of HDDs, with about 30 percent of the global HDD production lost and causing worldwide shortages of HDDs (Zhang, 2011b). Following the floods, some HDD manufacturers decided to change their manufacturing strategy, shifting manufacturing to other facilities outside of Thailand, while others decided that the benefits of the Thailand cluster were too great to move production (Romero, 2012).

While diversifying the supply base has been identified as an effective strategy for disruption management (Aydin et al., 2011; Tomlin & Wang, 2011), the benefits gained through diversification rely upon the assumption that when one supplier is disrupted the alternate supplier(s) continue to operate. This assumption is no longer valid if a disruption affects multiple suppliers, such as was the case of the HDD suppliers in Thailand. Therefore, because regional supply disruptions increase the probability of multiple suppliers being disrupted simultaneously (disruption correlation), the value of diversification decreases.

Because shared geographic location is a common source of failure correlation due to events such as natural disasters, political instability, and economic recessions, sourcing from different geographical regions eliminates this disruption correlation. Therefore, just as diversifying the supply base is an effective strategy for managing supplier disruptions, regional diversification is an effective strategy for managing regional (common cause) disruptions. Yet, while regional diversification reduces the risk of regional disruptions, it also can increase the cost and complexity of the supply chain.

This study is an attempt to identify the behavioral biases that may arise when simultaneously managing supplier and regional disruptions. I use behavioral experiments to investigate how decision makers use of supplier and regional diversification to mitigate against supplier and regional disruptions and how experiencing these disruptions affect sourcing
decisions. I develop theoretical models for the cost of sourcing from one region and two regions. Specifically, in the models, a single firm needs to source a fixed number of parts from a set of two homogeneous regions, with each region consisting of two homogeneous suppliers. Each region has a known probability of being disrupted, in which case none of the suppliers can deliver any parts. With no regional disruption, each supplier has a known risk of being disrupted, in which case the supplier cannot deliver any parts. Decision makers must balance the cost of diversification (both supplier and regional) with cost of a supply disruption (both supplier and regional). While supply base rationalization results in lower fixed costs due to fewer suppliers and/or regions, the cost of a disruption is more severe. The experimental design fixes all parameters except for the cost of sourcing from a region ($25, $50, $75), which changes the optimal sourcing decision to sourcing from two suppliers and one, one or two, and two regions, respectively. I find that decision makers tend to under-diversify both the number of suppliers and the number of regions, relative to the normative benchmark. Furthermore, disruptions of either type do not significantly affect sourcing decisions.

This paper proceeds as follows. I first develop theoretical models for sourcing from one and two regions. Next, I detail the research hypotheses and the supporting theory. I then discuss the experimental design and implementation, followed by the results of the laboratory study. Finally, I summarize my findings and provide managerial insights.

**Literature Review**

Recent high-profile events like the flooding in Thailand in 2011, the earthquake and tsunami in Japan in 2011, Hurricane Katrina in the Gulf region of the United States in 2005, and the earthquake in Taiwan in 1999, have motivated researchers to study the management of high-impact, low-probability risks in supply chains (S Chopra & Sodhi, 2004; Kleindorfer & Saad,
One particular area of focus has been order allocation in the face of supply side risk (Dada, Petruzzi, & Schwarz, 2007; Schmitt & Tomlin, 2009; Tomlin, 2006). This literature has since expanded to include multiple potential suppliers (Chaturvedi & Martinez-de-Albeniz, 2011; Sarkar & Mohapatra, 2009) and different types of disruption risk (Meena, Sarmah, & Sarkar, 2011; Sarkar et al., 2013).

Indeed, multiple sourcing is an effective strategy for managing supply chain disruptions (Kleindorfer & Saad, 2005; Sheffi, 2001; Tang, 2006; M Treleven & Schweikhart, 1988), reducing the exposure to costly supply disruptions (Sarkar et al., 2013) at the expense of efficiencies gained through increased economies of scale (Choi & Krause, 2006; Monczka et al., 1993; Trent & Monczka, 1998). Supplier selection studies have typically focused on two forms of risk, supply risk, where a disruption results in the supplier not being able to deliver the order (Chaturvedi & Martinez-de-Albeniz, 2011; Ruiz-Torres & Mahmoodi, 2007; Tomlin, 2006; Yang, Aydin, Babich, & Beil, 2008; Yu, Zeng, & Zhao, 2009), and yield risk, where the reliability of a supplier results in a shortage of material (Agrawal & Nanmias, 1997; Babich, Burnetas, & Ritchken, 2007; Maqbool Dada, Petruzzi, & Schwarz, 2007), or a combination of the two (Sunil Chopra, Reinhardt, & Mohan, 2007; Federgruen & Yang, 2008; Gurnani et al., 2013).

In contrast to this research, where supply disruptions are unique to each supplier, there is a limited number of research examining sourcing decisions when the supplier faces multiple forms of supply risk: specifically, where suppliers are not only individually at risk of being disrupted, but also where multiple suppliers are at risk of being disrupted and failing to deliver due to a common source of disruption (i.e. natural disaster, labor dispute, economic collapse, etc.). For example, Sarkar & Mohapatra (2009) examine optimal sourcing decisions when suppliers face multiple types of supply disruption, including *semi-super-events* that are location specific and *unique-events* that are supplier specific. They find that the probabilities of such events determine the optimal number of locations and suppliers. One critical assumption of their
model is that the probability of unique supply disruptions is equal in each location. Sarkar et al. (2013) refine the Sarkar & Mohapatra (2009) model, assuming unique disruption probabilities for each supplier. They propose a solution procedure to determine the optimal number of locations from which to source and the number of suppliers to source from each location.

While such theoretical models are intended to support decision makers in determining the optimal supply chain strategy, I am interested in investigating how sourcing decisions are made. This work contributes to the growing body of literature in Behavioral Operations Management research. Within this body of literature, there have been a number of studies examining managerial decision making in the presence of unknown demand (Bolton & Katok, 2008; Kremer et al., 2011; Lurie & Swaminathan, 2009; Schweitzer & Cachon, 2000), but research regarding supply uncertainty remains limited.

Recent work by Gurnani et al. (2013) examines sourcing decisions in a two-supplier setting, where one supplier is more reliable (and more costly) and one supplier is less reliable (and less costly). Because the marginal cost of a lost sale is constant and equal to the lost margin, it is always optimal to single source, sourcing exclusively from the reliable (unreliable) supplier taking into account the combination of cost and reliability. In contrast, Goldschmidt et al. (2014) utilize a model where suppliers have identical fixed costs and disruption probabilities, and the marginal cost of missing a sale is marginally increasing. They find evidence that the frequent reinforcement of supplier fixed costs and infrequent reinforcement of the cost of supply disruptions leads to an oscillating sourcing pattern, where decision makers temporarily increase their supply base following a severe supply disruption, and decrease their supply base as time passes without a supply disruption. Furthermore, they find that this oscillating sourcing pattern and the infrequent occurrence of supply disruptions leads decision makers to under-diversify their supply base. I build upon the work of Goldschmidt et al. (2014), investigating multiple levels of
sourcing decisions, unique and location based, when each supplier is at risk for unique supply disruptions and each location is at risk for a regional disruption.

**Theoretical Model**

While there exist different strategies for mitigating against supply disruptions, this study focuses on supply diversification either through supplier diversification or a combination of supplier and regional diversification. I first present a model for one region, where there are two suppliers \( (n) \) available to source from. Second, I present a model for two regions, where there are two regions \( (r) \), with two suppliers \( (n) \) available in each region (for a total of four suppliers).

So as to only focus on sourcing decisions, I set demand \( (D) \) to be deterministic. There exist \( N \) homogeneous suppliers from which the decision maker allocates demand, sourcing equally among the suppliers, but not necessarily equally among regions (i.e. sourcing from one region or sourcing from two regions and three suppliers). Each supplier faces an independent and identical probability of a disruption \( (p_s) \) and each region faces an independent and identical probability of a disruption \( (p_r) \). If a supplier is disrupted, then that supplier is unable to deliver in that round, and if a region is disrupted, then none of the suppliers in that region are able to deliver in that round. I model the marginally increasing cost of missed sales as:

\[
\tau = D - Y(n) \frac{D}{n}
\]

where \( \tau \) is the number of units short of demand and \( Y(n) \) is the number of deliveries received, following a binomial distribution. The total cost incurred in each round is the sum of the fixed costs of sourcing from \( n \) suppliers \( (\delta n) \) from \( r \) regions \( (\gamma r) \) and the expected cost of supply disruptions when sourcing from \( n \) suppliers \( (\alpha \tau^2) \), a quadratic cost function which captures all consequences of missed sales.
\[ C(n) = \delta n + \gamma r + \alpha r^2 \]

**Sourcing from a single region**

I can establish that when sourcing from a single region the probability of receiving deliveries is:

\[ Y(n, r = 1) = \begin{cases} X(n, r = 1) & \text{w.p. } (1 - p_r) \\ 0 & \text{w.p. } p_r \end{cases} \]

Following the binomial distribution, I can establish that:

\[
E[Y(n, r = 1)] = n(1 - p_s)(1 - p_r)
\]

\[
Var[Y(n, r = 1)] = n(1 - p_s)(1 - p_r)(p_s + np_r + np_s p_r)
\]

\[
E[Y^2(n, r = 1)] = n(1 - p_s)(1 - p_r)(n + p_s + n_1 p_s)
\]

Given sourcing from a single region \( r \), and the quadratic disruption cost and the probability (\( p \)) that a supplier faces a disruption, I can rewrite the expected cost function as:

\[
C(n | (r = 1)) = \delta n + \gamma + \alpha \left[ D^2 - 2Y(n) \frac{D^2}{n} + Y^2(n) \frac{D^2}{n} \right]
\]

\[
C(n | (r = 1)) = \delta n + \gamma + \alpha D^2 \left[ p_s^2 + p_r - p_s^2 p_r + \frac{p_s(1 - p_s)(1 - p_r)}{n} \right]
\]

**Sourcing from two regions**

I can establish that when sourcing from two regions the probability of receiving deliveries is:

\[ Y(n, r = 2) = \begin{cases} X(n, r = 1) & \text{w.p. } (1 - p_r)^2 \\ X(n, r = 2) & \text{w.p. } 2p_r(1 - p_r) \\ 0 & \text{w.p. } p_r^2 \end{cases} \]
Following the binomial distribution, I can establish that:

\[
E[Y(n, r = 2)] = n_1 p_r (1 - p_s) (1 - p_r) + n_2 p_r (1 - p_s) (1 - p_r) \\
+ (n_1 + n_2) (1 - p_s) (1 - p_r)^2
\]

\[
Var[Y(n, r = 2)] = (1 - p_s) (1 - p_r) (n_1 p_s + n_2 p_s + n_1^2 p_r + n_2^2 p_r - n_1^2 p_s p_r - n_2^2 p_s p_r)
\]

\[
E[Y^2(n, r = 2)] = (n_1 + n_2)^2 (1 - p_s)^2 (1 - p_r)^2 + (n_1 + n_2) p_s (1 - p_s) (1 - p_r)^2 + n_1^2 p_r (1 - p_r) (1 - p_s)^2 + n_1 p_s p_r (1 - p_s) (1 - p_r) + n_1 p_s p_r (1 - p_s) (1 - p_r)
\]

Given sourcing from a two regions \( r = 2 \) and the quadratic disruption cost and the probability \( p \) that a supplier faces a disruption, I can rewrite the expected cost function as:

\[
C(n| r = 2) = \delta(n_1 + n_2) + 2\gamma + \alpha \left[ D^2 - 2Y(n) \frac{D^2}{(n_1+n_2)} + Y^2(n) \frac{D^2}{(n_1+n_2)} \right]
\]

\[
C(n| r = 2) = \delta(n_1 + n_2) + 2\gamma + \alpha D^2 \left[ 1 - \frac{(1-p_s) (1-p_r)}{(n_1+n_2)} \right] \left[ 2n_1 p_r + n_2 p_r + (n_1 + n_2)(1 - p_r) + \frac{(1-p_s)(1-p_r)}{(n_1+n_2)} \left( (n_1 + n_2)^2 (1 - p_s) (1 - p_r) + (n_1 + n_2) p_s (1 - p_r) + n_1^2 p_r (1 - p_s) + n_1 p_s p_r + n_2 p_s p_r \right) \right]
\]

In order to determine the theoretical optimal number of regions to source from, one must compare the cost of sourcing from one and two regions, with the total number of suppliers, and other parameters are set equal.

**Hypotheses**

There is much uncertainty surrounding supply disruptions, with many unknown factors, including timing and severity of such events. That said, procurement managers should have an understanding of the supply chain and the associated risks, assigning probabilities to these risks and assessing the impact should a supply disruption occur. Provided with such information, the
optimal sourcing decision can be calculated by procurement managers. This decision should be determined by calculating the marginal benefits of adding or subtracting a supplier or region with the marginal costs of doing so. Such calculations should be independent of previous outcomes, but previous research has shown that decision makers tend to draw conclusions based on recent outcomes (Tversky & Kahneman, 1974).

Prior research has shown that decisions are often biased, and as a result numerous models have been developed to explain these biases. In a closely related paper, Goldschmidt et al. (2014), observe an oscillating pattern of diversification, with decision makers diversifying their supply base following costly supply chain disruptions and consolidating their supply base over time with no disruption. This oscillating pattern of sourcing is attributed to reinforcement, where reinforcement of the value of diversification only occurs following a disruption. Unlike Goldschmidt et al. (2014), where there is only the risk of unique supplier disruptions, subjects in the experiment from this paper have multiple diversification alternatives and face multiple disruption risks, including both unique, supplier disruptions, and common cause, regional disruptions.

While my theoretical model predicts that decision makers should make the same choice every round, prior research suggests that decision makers follow an adaptive process in which prior outcomes affect future decisions (Hertwig et al., 2004). This adaptive behavior is commensurate with system neglect, where decisions are driven more by the signals than by the system generating the signal (Kremer et al., 2011; Massey & Wu, 2005). This reinforcement learning behavior drives decisions that have resulted in more favorable outcomes in the past. Since the probability of disruption is low, the value of diversification is rarely reinforced, leading decision makers to under diversify their supply base on average.

**Hypothesis 1 (Under-Diversification).** Decision makers will under-diversify their supply base.
The theoretical model includes a linearly increasing fixed cost of regional sourcing, similar to the fixed cost of supplier diversification. Intuitively, the theoretical model illustrates that increasing the cost of regional sourcing increases the expected total cost. As the cost of regional sourcing increases, the value of regional diversification decreases. Therefore, I posit that increasing the cost of regional sourcing will decrease the likelihood of sourcing from multiple regions.

**Hypothesis 2 (Sensitivity of Regional Diversification Cost).** *As the cost of regional sourcing decreases (increases), a larger (smaller) proportion of decision maker’s orders will be diversified among multiple regions.*

Following the theoretical model, including a fixed cost of sourcing from a region and a probability of regional disruption adds an additional layer of complexity to both the fixed cost, disruption cost, and the frequency of disruption. This complexity further complicates the salience of these parameters. First, including an additional region includes adding both a fixed cost of an additional supplier along with another fixed cost of sourcing from an additional region. While the fixed cost calculation remains linear, it is increasingly difficult to calculate when sourcing from multiple suppliers and regions. Next, in the single disruption model of Goldschmidt et al. (2014), the probability of a supplier (or multiple suppliers) experiencing a supply chain disruption is relatively easily calculated (or at least estimated), but when an additional layer of risk is included, the probability of a supplier, or multiple suppliers, being disrupted becomes more difficult to calculate. Lastly, calculating the cost of a supply chain disruption becomes increasingly difficult as well as the number of available suppliers increases. Taken together, the additional fixed cost of regional procurement, the increased difficulty in calculating the probability of disruption(s) and
the increased number of suppliers combine to make calculating the expected cost of a sourcing decision increasingly difficult.

The increased complexity of the problem is likely to lead decision makers to become more reliant on decisions from experience. Because there are multiple types of disruptions and ways to mitigate against these disruptions, I hypothesize that decision makers will respond uniquely to each disruption, with a supplier disruption prompting supplier diversification, and a regional disruption prompting regional diversification. Having diversified the supply base, either through supplier or regional diversification, without reinforcement of disruptions, decision makers will consolidate their supply base.

**HYPOTHESIS 3A (SUPPLIER DIVERSIFICATION).** Following a severe supplier disruption, decision makers increase the number of suppliers.

**HYPOTHESIS 3B (REGIONAL DIVERSIFICATION).** Following a severe regional disruption, decision makers increase the number of regions.

**HYPOTHESIS 4 (CONSOLIDATION).** Without a disruption decision makers will consolidate their supply base.

**Experimental Design and Implementation**

I conduct repeated decision experiments using zTree (Fischbacher, 2007), where decision makers must determine the number of suppliers \( n \) and regions \( r \) to source from in 100 successive rounds (See Appendix D). In each round, demand \( D = 100 \) is allocated equally among the \( n \) homogeneous suppliers. Each supplier faces an independent and identical probability of a disruption \( p_s = 0.01 \) and each region faces an independent and identical
probability of a disruption \( p_r = 0.01 \). If a supplier is disrupted, due to either a supplier or regional disruption, then that supplier is unable to deliver the \( \left( \frac{D}{n} \right) \) units.

In this study, I hold constant the fixed cost of sourcing from a supplier \( \delta = 25 \) and the constant \( \alpha = 1.01 \) in the expected disruption cost function. I vary the cost of sourcing from a region \( r \in \{25, 50, 75\} \) between subjects. With these parameter values, Figure 3-1 plots the total expected cost of sourcing from the available regions and suppliers. I label the supplier and region selection options as \( 1S1R \) (One Supplier in One Region), \( 2S1R \) (Two Suppliers in One Region), \( 2S2R \) (Two Suppliers in Two Regions), \( 3S2R \) (Three Suppliers in Two Regions), and \( 4S2R \) (Four Suppliers in Two Regions).

![Figure 3-1: Total Expected Cost of Sourcing Decisions.](image)

In Figure 3-1, I observe that the minimum total expected cost reflects sourcing from two suppliers and one region \( r = 75 \), either one or two regions \( r = 50 \), or two regions \( r = 25 \), which are referred to as \( 1R, IR, \) and \( 2R \), respectively. Such a design allows for examining how
decision makers use various forms of diversification to mitigate against supply disruptions and how changes to sourcing decisions affect the expected profitability.

In each of the 100 rounds, the subject’s decision was to choose how many suppliers, $n$, and how many regions, $r$, to source from. After submitting the choice, the results of that round were provided to the subject as both cost data and a visual representation of the random outcomes of regional or supplier disruptions (See Appendix D). The disruption information was provided for suppliers and regions that were utilized by the subject, and the counterfactual information was provided for suppliers and regions that were not utilized by the subject. Providing full information to the subjects eliminated the chance that subject sourcing decisions were made to increase information about disruption probabilities.

The experiment was conducted in the behavioral laboratory at a large public university. Subjects were recruited from the introductory course in Supply Chain Management and compensated with extra credit for the course and the potential to earn cash for their participation. Prior to the experiment, subjects were provided with an instruction sheet, explaining the task and including formulas and illustrative examples of the fixed cost and realized cost of a supply disruption (See Appendix C). Subjects were provided with an initial endowment, equal to $50 USD and their objective was to minimize their total costs (both fixed and disruption costs) over the course of the 100 rounds. The endowment was set such that the minimum earnings of the experiment was $0 USD, thus avoiding any chance of bankruptcy prior to the completion of the experiment (Friedman & Sunder, 1994). The final potential earnings were calculated as the endowment minus the total accrued costs of the subject across the 100 rounds of the experiment and then converted from laboratory dollars to USD for payment. Following the experiment, two subjects were randomly drawn from each course section and paid their experiment earnings. The average subject earnings in the experiment was $42, with a maximum subject earnings of $52 and a minimum subject earnings of $20.
Results

I present the summary statistics in Table 3-1. First, I test observed sourcing decisions of number of regions and number of suppliers against the theoretical predictions observed in Figure 3-1. For the number of regions, I observe a significant difference between the observed number of suppliers and the predicted number of suppliers for all three conditions: 1R (Wilcoxon Test, p<0.01), IR (p<0.01), and 2R (p<0.01). Next, for the number of suppliers, I observe a significant difference between the observed number of suppliers and the predicted number of suppliers, which is two suppliers for all three conditions: 1R (Wilcoxon Test, p<0.01), IR (p<0.01), and 2R (p=0.01). Consistent with Hypothesis 1 (Under-Diversification), these results suggest that decision makers under-diversify both suppliers and regions, on average. While under-diversifying the supply base leads to a reduction in supply disruptions, disruptions are costlier and this sub-optimal sourcing results in decision makers incurring additional expected costs.

Table 3-1: Summary Statistics.

<table>
<thead>
<tr>
<th>Measure</th>
<th>2R</th>
<th>IR</th>
<th>1R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Regions</td>
<td>1.22</td>
<td>1.16</td>
<td>1.26</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(0.37)</td>
<td>(0.44)</td>
</tr>
<tr>
<td>Number of Suppliers</td>
<td>1.40</td>
<td>1.32</td>
<td>1.45</td>
</tr>
<tr>
<td></td>
<td>(0.58)</td>
<td>(0.62)</td>
<td>(0.79)</td>
</tr>
<tr>
<td>Total Fixed Cost</td>
<td>$65.32</td>
<td>$91.00</td>
<td>$130.42</td>
</tr>
<tr>
<td></td>
<td>($23.15)</td>
<td>($31.59)</td>
<td>($49.96)</td>
</tr>
<tr>
<td>Total Penalty Cost</td>
<td>$100.00</td>
<td>$100.00 or $150.00</td>
<td>$125.00</td>
</tr>
<tr>
<td></td>
<td>($1213.46)</td>
<td>($1310.11)</td>
<td>($1142.37)</td>
</tr>
<tr>
<td>Total Cost</td>
<td>$204.62</td>
<td>$254.62</td>
<td>$279.63</td>
</tr>
<tr>
<td></td>
<td>($1212.77)</td>
<td>($1309.13)</td>
<td>($1142.18)</td>
</tr>
<tr>
<td>Expected Cost Ratio</td>
<td>1.11</td>
<td>1.08</td>
<td>1.09</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.04)</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

Notes. Standard deviation is in parentheses and the theoretical optimal value is italicized.
Next, I test observed cost measures against the theoretical predictions. I find that the observed total fixed cost significantly differs from the predicted fixed for Conditions 1\(R\) (Wilcoxon Test, \(p<0.01\)) and 1\(IR\) (\(p<0.01\)), but does not significantly differ for Condition 2\(R\) (\(p=0.76\)). Alternatively, I find that the observed total penalty cost does not significantly differ from the predicted penalty cost: 1\(R\) (Wilcoxon Test, \(p=0.11\)), 1\(IR\) (\(p=0.20\)), and 2\(R\) (\(p=0.49\)). Combining the total fixed cost and total penalty cost, similar to the independent results, I find that the observed total cost does not significantly differ from the predicted total cost: 1\(R\) (Wilcoxon Test, \(p=0.49\)), 1\(IR\) (\(p=0.91\)), and 2\(R\) (\(p=0.70\)). Lastly, I calculate the Expected Cost Ratio, defined as \(\frac{c(R_i \cap c_{t,t})}{c(c_{t,t}^\ast)}\), and find that on average, subjects incurred between 8 and 11 percent additional cost by not sourcing from the theoretical optimal number of suppliers or regions.

I next analyze the effect of the fixed cost of regional diversification has on the likelihood of sourcing from multiple regions. In Table 3-1, I observe that overall, subjects consistently sourced from less than two regions and it appears that the level of regional diversification does not significantly vary across conditions. To formally test this, I estimate a logistic regression model,

\[
\Pr(\text{Regions} = 2) = \Phi[\beta_0 + \beta_1 y_i].
\]

I observe in Table 3-2 that the regional fixed cost of diversification has no significant effect on the likelihood of sourcing from multiple regions. This result is surprising because the cost of regional diversification was varied such that the optimal sourcing decision is to source from one region, indifference between sourcing from one and two regions, and source from two regions. Therefore, I fail to find support for Hypothesis 2, that increasing (decreasing) the cost of regional diversification decreases (increases) the likelihood of sourcing from multiple regions.

Table 3-2: Likelihood of Sourcing from Multiple Regions.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.60**</td>
</tr>
</tbody>
</table>
Lastly, I am interested in supplier diversification and consolidation in response to supply disruptions. In order to formally test patterns of changes to sourcing decisions following regional supply disruptions, I fit the logistic regression,

$$\text{Pr}(r_{i,t} = 2) = \Phi[\beta_{SR} + \beta_{DR}DR_{i,t-1} + \beta_{ER}ER_{i,t-1} + \beta_{DRE}DR_{i,t-1}ER_{i,t-1} + \beta_{t}]$$

(2)

where $DR_{i,t-1}$ is an indicator variable for subject $i$ sourced from two regions in round $t-1$, $ER_{i,t-1}$ is an indicator variable for subject $i$ experiencing a regional supply disruption in round $t-1$, and $DR_{i,t-1}ER_{i,t-1}$ is the corresponding interaction effect. Furthermore, I include round $t$ which captures any learning effects over the course of the experiment. I estimate Equation (2) separately for each of the three conditions in the experimental design. The results are presented in Table 3-3.

### Table 3-3: Estimation Results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Condition 1R</th>
<th>Condition IR</th>
<th>Condition 2R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-2.21**</td>
<td>-2.77**</td>
<td>-2.06**</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.23)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Sourced from Two Regions</td>
<td>3.25**</td>
<td>2.97**</td>
<td>2.78**</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.44)</td>
<td>(0.53)</td>
</tr>
<tr>
<td>Region Disrupted</td>
<td>1.25*</td>
<td>-0.10</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(0.67)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>Sourced from Two Regions and</td>
<td>0.09</td>
<td>0.20</td>
<td>-0.54</td>
</tr>
<tr>
<td>Experienced a Regional Disruption</td>
<td>(1.14)</td>
<td>(0.89)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>Round</td>
<td>-0.002</td>
<td>-0.005</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Notes. Robust standard errors are in parentheses. **p≤0.01, *p≤0.05.

Across all three conditions, I find strong evidence of decision continuity. Following rounds without a regional disruption, decision makers that sourced from one region were overwhelmingly likely to continue sourcing from one region ($\beta_{SR} < 0, p < .01$), in each of the
three conditions. Similarly, following rounds without a regional disruption, decision makers that sourced from two regions were likely to continue sourcing from two regions ($\beta_{SR} + \beta_{DR} > 0, p < .01$). To formally test Hypothesis 4 (Consolidation), I compare the relative magnitude of $\beta_{SR}$ (repeat sourcing from one region) and $\beta_{SR} + \beta_{DR}$ (repeat sourcing from two regions). I find that over rounds without a disruption event, decision makers that sourced from two regions are more likely to reduce the number of regions sourcing from than decision makers that sourced from a single region are likely to diversify the number of regions sourcing from. Taken together, these effects result in a reduction in the number of regions, supporting Hypothesis 4.

Interestingly, I only observe of decision makers changing their regional sourcing decisions following a regional supply disruption in Condition 1R, and therefore fail to find support for Hypothesis 3B (Regional Diversification).

In order to formally test patterns of changes to sourcing decisions following supplier disruptions, I fit the multinomial logistic regression,

$$\Pr(n_{i,t} = 1) = \Phi[\beta_l + \beta_n n_{i,t-1} + \beta_E E_{i,t-1} + \beta_t t]$$

(3)

where $n_{i,t-1}$ is the number of suppliers that subject $i$ sourced from in round $t-1$, $E_{i,t-1}$ is an indicator variable for subject $i$ experiencing a supplier disruption in round $t-1$, and $t$ captures any learning effects. I estimate Equation (3) separately for each of the three conditions and present the results in Table 3-3.

Table 3-3: Estimation Results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Condition 1R</th>
<th>Condition IR</th>
<th>Condition 2R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept 2</td>
<td>4.27**</td>
<td>3.41**</td>
<td>3.91**</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(0.41)</td>
<td>(0.77)</td>
</tr>
<tr>
<td>Intercept 3</td>
<td>7.46**</td>
<td>6.46**</td>
<td>7.35**</td>
</tr>
<tr>
<td></td>
<td>(1.02)</td>
<td>(0.83)</td>
<td>(1.08)</td>
</tr>
<tr>
<td>Intercept 4</td>
<td>8.45**</td>
<td>7.16**</td>
<td>10.10**</td>
</tr>
<tr>
<td></td>
<td>(1.05)</td>
<td>(0.96)</td>
<td>(1.60)</td>
</tr>
<tr>
<td>Supplier Sourcing Decision Previous Round</td>
<td>-2.50**</td>
<td>-2.01**</td>
<td>-2.43**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Consistent with Hypothesis 4 (Consolidation), across all three conditions, I find strong evidence for decision makers being more likely to single source following rounds without a supplier disruption than continue sourcing from a diversified supply base. Furthermore, the likelihood of single sourcing increases with the level of diversification in the previous round. Additionally, consistent with regional supply disruptions, following a unique supplier disruption, I fail to find evidence of supplier diversification, observing that there is no significant change in the estimated log-odds following the experience of a supplier disruption. I therefore find no support for Hypothesis 3A (Supplier Diversification).

**Conclusion**

In this study, I examined sourcing decisions, supplier diversification and regional diversification, in the presence of two forms of supply risk: supplier disruptions and regional supply disruptions. Using controlled laboratory experiments, I examine supplier and regional diversification decisions in three experimental conditions: when it is optimal to source from two suppliers and one region, two suppliers and either one or two regions, and two suppliers and two regions. Across all conditions, I find evidence of under-diversification of both suppliers and regions. This under-diversification can be attributed to the observation that decision makers are overwhelmingly likely to source from a single supplier and a single region, even following supply chain disruptions.
These results are partially supported by the predictions of reinforcement of recent sourcing decisions, but the additional complexity of common cause disruptions on top of supplier disruptions leads decision makers to not increase their supply base following either supplier or regional supply chain disruptions. The lack of supplier or regional diversification following supply chain disruptions suggests that the complexity of the problem leads decision makers to question the value of both supplier and regional diversification.

As observed in this experiment, persistent reliance on a sourcing strategy can be costly in the long run. This research suggests that in complex sourcing environments, decision makers fail to understand the value of diversification, under-diversifying the supply base as a way to manage complexity, even if it erodes expected profitability. This finding is important because sourcing managers often must consider multiple disruption threats, some of which are correlated, when determining the appropriate sourcing strategy for their organization.

Because these complex sourcing and disruption environments lead decision makers to under-diversify as a way of controlling for complexity, greater support should be provided to sourcing managers to help understand these complex environments. This support should provide a greater understanding of how sourcing managers can mitigate against potential disruption threats. While understanding the complex sourcing environment should lead sourcing managers to make better procurement decisions, these decisions should be reviewed periodically, both during periods without disruptions and following supply chain disruptions. Such periodic reviews of sourcing policies serve to further reinforce awareness of disruption mitigation strategies.
Chapter 4

Conclusion and Future Research

This dissertation set out to investigate how behavioral biases impact sourcing decisions when the supply chain is at risk of low probability disruptions. In this final chapter, I will review the research contributions of this dissertation and discuss future research.

Contributions

This research makes contributions to the emerging field of behavioral operations. In Chapter 2, I found evidence of an oscillating pattern of supplier diversification, where the supply base is temporarily increased following the experience of a severe supply disruption, followed by a gradual decrease of the supply base as time passes with no further disruptions. I suggest that this oscillating sourcing pattern is due to the lack of reinforcement of the cost of supply disruptions, ultimately leading to an under-diversified supply base. In order to break this oscillating cycle of supply base diversification and consolidation, I recommend regular stress tests that evaluate the impact of supply chain disruptions.

In Chapter 3, I investigate sourcing decisions when multiple sourcing diversification strategies are available, as well as multiple forms of disruption risk. I find further evidence of supply base under diversification, but no evidence of the oscillating pattern of supplier diversification in this more complicated setting. The data suggest that decision makers mostly adhere to their adopted sourcing strategy, switching to suppliers that are perceived to be less likely to be disrupted. This research suggests that too much attention is given to particular supplier performance, rather than to whether the most appropriate strategy is in place.
Future Research

This dissertation focused on one method of supply chain resiliency against disruptions: supplier diversification. While supplier diversification is an effective strategy in managing supply chain disruptions, it is not the only strategy available to procurement managers. Future studies will expand upon supplier diversification and introduce inventory decisions to understand whether there is a preferred sourcing strategy and how procurement managers use this strategy alone and in collaboration with supplier diversification.
References


Appendix A

Sample Instructions

You are about to participate in an experiment in the economics of individual decision making. If you follow these instructions carefully and make good decisions, you will earn money that will be paid to you in cash at the end of the session. If you have a question at any time, please raise your hand and the research investigator will answer it. I ask that you not talk with one another for the duration of the experiment.

Task Description

You will be playing the role of a procurement manager of a firm. In each of a total of 200 periods, the firm’s customers demand 100 units of a product which requires procuring “wodgets” as input material – with one wodget necessary for unit you produce. Your task is to procure the required 100 wodgets from the firm’s suppliers. Specifically, the firm has 2 potential suppliers and you need to decide how to allocate the total procurement of 100 wodgets among these suppliers. For example, if you decide to procure from a single supplier, then you would order all 100 units from that supplier. Alternatively, if you decide to procure from both suppliers, then you would order 50 units from each of them.

Supplier Disruptions

In each period, every supplier is at risk of being disrupted by an external event (e.g. a fire in the supplier’s factory). If disrupted, the supplier would not deliver any wodgets in that period. For example, imagine you procure the 100 wodgets from one supplier, if this supplier experiences a disruption, then in that period you will be 100 wodgets short of what you need. Alternatively, imagine you procure the 100 wodgets from two suppliers, i.e., 50 wodgets from each of them. If one of these suppliers experiences a disruption, then in that period you will be 50 wodgets short of what you need. While you cannot influence whether a supplier is disrupted or not, you do know the probability of it happening. Specifically, you know that any given supplier is disrupted with a probability of 1%. This means that a supplier cannot deliver 1 out of every 100 periods on average. However, note that disruptions are random – it is possible that a supplier is never disrupted, but it could happen that a supplier is disrupted 5 times (although this is not very likely), or even 13 times (this is even less likely).

Total Procurement Cost

Your supplier selection decision affects two cost components. First, you incur a fixed cost of $50 for every supplier that you procure wodgets from in a given period:

\[
\text{Total Fixed Cost} = 50 \times (\text{Number of suppliers you procure from})
\]
For example, if you decide to procure from two suppliers, then you would incur a total fixed cost of $100 (=50*2) in that period. Importantly, you incur the fixed cost even if the supplier is disrupted and does not deliver any wodgets.

Second, you incur a disruption cost when any of your selected suppliers is disrupted and does not deliver wodgets. You incur a disruption cost for every wodget short of the 100 wodgets that you need, for not being able to produce the final product for your customers. The more wodgets you fail to procure because of disruptions at your supplier(s), the larger the total disruption cost. The total disruption cost increase is quadratic in the number of wodgets not received:

$Total\ Disruption\ Cost = \$1 \times (Number\ of\ wodgets\ not\ received)^2$

Importantly, note that you incur disruption costs only if (at least) one of your selected suppliers experiences a disruption. Furthermore, note that the magnitude of the disruption cost would depend on how many suppliers you decided to procure from.

Please carefully study the following table, which provides you with the realized (fixed and disruption) costs for different scenarios, for a single period.

<table>
<thead>
<tr>
<th>Sourcing Decision</th>
<th>Source 100 wodgets from a single supplier</th>
<th>Source 50 wodgets from each supplier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Fixed Cost</td>
<td>$50</td>
<td>$50+$50=$100</td>
</tr>
<tr>
<td>Total Disruption Cost with NO Supplier Disrupted</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total Disruption Cost with ONE Supplier Disrupted</td>
<td>$10,151 (shortage of 100 wodgets)</td>
<td>$2,625 (shortage of 50 wodgets)</td>
</tr>
<tr>
<td>Total Disruption Cost with TWO Suppliers Disrupted</td>
<td>n/a</td>
<td>$10,151 (shortage of 100 wodgets)</td>
</tr>
</tbody>
</table>

Your goal in this experiment is to minimize the total procurement cost, which is the sum of the fixed cost and any disruption cost incurred in each period:

$Total\ Procurement\ Cost = Total\ Fixed\ Cost + Total\ Disruption\ Cost$

**How I determine your payment**

At the end of the experiment, the computer will calculate your total earnings, by deducting the total procurement cost that you have accumulated across the 200 periods, from an endowment of $110,000 laboratory dollars given to you at the beginning of the experiment. The total earnings will then be converted to US dollars. Specifically, you will be paid $1.00 US dollars for every $5,000 laboratory of your total earnings in the experiment. On the final screen you will be able to see your total earnings in US dollars for this session. You will be paid in cash at the end of the session. All earnings are confidential, though you will have to sign a sheet indicating how much you have been paid.

**Important:** If at any point you have accumulated a total cost that exceeds your initial endowment of $110,000, the experiment will be terminated and your total earnings would be $0.
Appendix B

Screenshots of the User Interface

<table>
<thead>
<tr>
<th>Period</th>
<th>Suppliers selected</th>
<th>Total fixed cost</th>
<th>Suppliers disrupted</th>
<th>Total penalty cost</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>$60</td>
<td>0</td>
<td>$60</td>
<td>$60</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>$100</td>
<td>0</td>
<td>$100</td>
<td>$100</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>$100</td>
<td>1</td>
<td>$250</td>
<td>$300</td>
</tr>
</tbody>
</table>

Please make your selections

Order: 0 units  
Order: 0 units  

(Images of factory buildings with icons indicating orderung 0 units)
Total Penalty cost: $25.25
Total cost in this period: $29.25

Order: 50 units
Received: 50 units
Fixed cost: $50

Order: 50 units
Not Received: 50 units
Fixed cost: $50
Appendix C

Sample Instructions

You are about to participate in an experiment on decision making. The experiment is designed not to test your knowledge, but to learn about your decision making. All individual responses are completely confidential and anonymous. If you have any question, feel free to raise your hand.

Task Description

You will be playing the role of a procurement manager of a firm. In each of a total of 100 periods, the firm’s customers demand 100 units of a product which requires procuring “wodgets” as input material – with one wodget necessary for unit you produce. Your task is to procure the required 100 wodgets from the firm’s suppliers. Specifically, the firm has 4 potential suppliers, with 2 suppliers in each of the 2 regions and you need to decide how to allocate the total procurement of 100 wodgets among these regions and suppliers.

Supplier Disruptions

In each period, every region and supplier is at risk of being disrupted by an external event (e.g. an earthquake in a region or a fire in the supplier’s factory). If a region is disrupted, none of the suppliers in that region would be able to deliver any wodgets in that period. If there is no regional disruption but a supplier within the region is disrupted, the supplier would not deliver any wodgets in that period. For example, imagine you procure the 100 wodgets from one supplier, if this region (or supplier) experiences a disruption, then in that period you will be 100 wodgets short of what you need. Alternatively, imagine you procure the 100 wodgets from four suppliers, two in each region. If one of these regions experiences a disruption, then in that period you will be 50 wodgets short of what you need, but if there is no regional disruption but one supplier experiences a disruption, then in that period you will be 25 wodgets short of what you need. While you cannot influence whether a region or supplier is disrupted or not, you do know the probability of it happening. Specifically, you know that any given region is disrupted with a probability of 1% and any given supplier is disrupted with a probability of 1%. However, note that both regional and supplier disruptions are random and independent.

Total Procurement Cost

Your supplier selection decision affects two cost components. First, you incur a regional fixed cost of $25 for every region that you procure wodets from and a supplier fixed cost of $25 for every supplier that you procure wodgets from in a given period:

\[ \text{Total Fixed Cost} = 25 \times (\text{Number of regions you procure from}) + 25 \times (\text{Number of suppliers you procure from}) \]

For example, if you decide to procure from two suppliers among two regions, then you would incur a total fixed cost of $100 (=25*2+$25*2) in that period. Importantly, you incur the fixed cost even if the supplier is disrupted and does not deliver any wodgets.
Second, you incur a **penalty cost** when any of your selected suppliers is disrupted either due to a regional or supplier disruption and does not deliver wodgets. You incur a penalty cost for every wodget short of the 100 wodgets that you need, for not being able to produce the final product for your customers. The more wodgets you fail to procure because of disruptions at your supplier(s), the larger the total penalty cost. The total penalty cost increase is quadratic in the number of wodgets not received:

\[
\text{Total Penalty Cost} = 1 \times (\text{Number of wodgets not received})^2
\]

Importantly, note that you incur penalty costs only if (at least) one of your selected suppliers experiences a disruption. Furthermore, note that the magnitude of the penalty cost would depend on how many suppliers you decided to procure from.

Please carefully study the following table, which provides you with the realized (fixed and penalty) costs for different scenarios, for a single period.

<table>
<thead>
<tr>
<th>Sourcing Decision: Number of Regions</th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>2</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sourcing Decision: Number of Suppliers</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td><strong>Total Fixed Cost</strong></td>
<td>$50</td>
<td>$75</td>
<td>$100</td>
<td>$125</td>
<td>$150</td>
</tr>
<tr>
<td><strong>Total Penalty Cost with NO Supplier Disrupted</strong></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Total Penalty Cost with ONE Supplier Disrupted</strong></td>
<td>$10,309 (shortage of 100 wodgets)</td>
<td>$2,577 (shortage of 50 wodgets)</td>
<td>$2,577 (shortage of 50 wodgets)</td>
<td>$1,145 (shortage of 33 wodgets)</td>
<td>$644 (shortage of 25 wodgets)</td>
</tr>
<tr>
<td><strong>Total Penalty Cost with TWO Suppliers Disrupted</strong></td>
<td>n/a</td>
<td>$10,309 (shortage of 100 wodgets)</td>
<td>$10,309 (shortage of 100 wodgets)</td>
<td>$4,582 (shortage of 67 wodgets)</td>
<td>$2,577 (shortage of 50 wodgets)</td>
</tr>
<tr>
<td><strong>Total Penalty Cost with THREE Suppliers Disrupted</strong></td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>$10,309 (shortage of 100 wodgets)</td>
<td>$5,799 (shortage of 75 wodgets)</td>
</tr>
<tr>
<td><strong>Total Penalty Cost with FOUR Suppliers Disrupted</strong></td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>$10,309 (shortage of 100 wodgets)</td>
</tr>
</tbody>
</table>

Your goal in this experiment is to minimize the total procurement cost, which is the sum of the fixed cost and any penalty cost incurred in each period:

\[
\text{Total Procurement Cost} = \text{Total Fixed Cost} + \text{Total Penalty Cost}
\]

**How I determine your payment**

You can actually earn money in this experiment! 2 participants per course Section of SCM 301 will be chosen randomly and will be paid based on her/his profits. At the end of the
experiment, the computer will calculate your total earnings, by deducting the total procurement cost that you have accumulated across the 100 periods, from an endowment of $105,000 laboratory dollars given to you at the beginning of the experiment. The total earnings will then be converted to US dollars. Specifically, you will be paid $1.00 US dollars for every $2,000 laboratory of your total earnings in the experiment. On the final screen you will be able to see your total earnings in US dollars for this session.

**Important**: If at any point you have accumulated a total cost that exceeds your initial endowment of $105,000, the experiment will be terminated and your total earnings would be $0.
Appendix D

Screenshots of the User Interface
Period 13 out of 100

Total Penalty cost: $2577
Total cost in this period: $2727

Order: 25 units
Not Received: 25 units
Supplier fixed cost: $25

Order: 25 units
Received: 25 units
Supplier fixed cost: $25

Order: 25 units
Received: 25 units
Supplier fixed cost: $25

Order: 25 units
Received: 25 units
Supplier fixed cost: $25
VITA

Kyle Goldschmidt

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