Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 16, No. 1, Winter 2014, pp. 61–75
ISSN 1523-4614 (print) | ISSN 1526-5498 (online)

http://dx.doi.org/10.1287/msom.2013.0453

Ordering Behavior Under Supply Risk: An Experimental Investigation

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As supply chains become increasingly complex and global in their scale, supplier selection and management in the face of disruption risk has become one of the most challenging tasks for modern managers. Several novel model-based approaches to managing such risks have been developed in the academic literature, but how behavioral tendencies may affect procurement decisions under such conditions has received relatively less attention. In this paper, we present results from a study where paid subjects were asked to place orders from two suppliers who differ in their costs and risks to satisfy a fixed amount of end-customer demand. We show that under such a scenario, it is theoretically optimal to *sole source* either from the more reliable (and more costly) supplier or from the more risky but cheaper supplier, depending on cost and risk parameters. Subjects in our experiment, however, show a systematic tendency to *diversify* their orders between the two sources. We document this diversification tendency in procurement decisions and its possible impact on profits under various cost and risk settings as well as comment on various ordering behavior observed during the experiments. We also establish that bounded rationality of subjects can provide a possible rationale for the above phenomenon.

Key words: disruption management; supply risk management; experiments; ordering behavior; diversification bias; bounded rationality
History: Received: October 14, 2011; accepted: March 27, 2013. Published online in *Articles in Advance* October 23, 2013.

1. Introduction

Supply management in the face of disruption risk is an issue that modern managers face every day. In recent times, there have been several supply disruptions attributed to natural disasters. For instance, the spread of volcanic ash in Iceland in 2010 resulted in air transportation disruptions leading to component shortages at automakers such as Nissan and BMW (Miller 2010). More recently, earthquake and tsunami-related disruptions have resulted in severe shortage of products and spare parts manufactured in Japan (Fink 2011). Examples also abound of supply disruptions due to other factors such as political uncertainty, financial breakdown, weather, terrorism, and strikes (for more examples, see Tang 2006, Gumus et al. 2012, Sodhi et al. 2012). Indeed, such disruptions have been blamed for significantly lower operational performance and reduced profitability for firms (Hendricks and Singhal 2005).

As many North American companies have sought cheaper suppliers from developing countries, the risk associated with unproven suppliers has increased further. One particular decision facing managers in that context is how to allocate their orders between suppliers of differing costs and risks (e.g., a less risky but costly supplier from a developed country and a cheaper but more risky alternative from a developing country). This problem of order allocation in the face of supply risk, especially of the disruption type, has received significant attention in theoretical and empirical operations management (OM) literature. Several researchers have addressed such a procurement problem from a variety of perspectives (e.g., Hendricks and Singhal 2005, Gurnani and Shi 2006, Dada et al. 2007, Tomlin 2009, Yang et al. 2009, Yu et al. 2009, Gumus et al. 2012). But, many critical procurement decisions are influenced by behavioral tendencies of managers. This has been studied in newsvendor (for details, see §2) and in several other contexts.

For example, a field study by Anderson et al. (2000) shows that valuation of nonmonetary attributes by procurement professionals is affected by their perceptions. Carter et al. (2008) survey procurement professionals and compare the survey findings to objective data; they find that selection of suppliers from low-cost countries are influenced significantly by biases and perceptions of those professionals. Purchasing behavior of managers in the presence of supply risk has also been discussed by Zsidisin (2003), Smith (2009), and Ellis et al. (2010) (we discuss this in more detail in §2). However, *experimental investigation* of ordering behavior focusing on supply disruption risk is limited in the extant literature. In this paper, we address this gap by comparing theoretical predictions with decisions made by subjects in an experimental setting.

We first develop a theoretical model to establish the optimal procurement strategy of a risk-neutral buyer facing constant demand. The buyer has the option of buying from two suppliers, one of which (say, R) is less risky but more costly compared to the other (say, U). Given our model setting, the optimal strategy for the buyer is to procure from only one of the two suppliers (i.e., *sole sourcing*). Specifically, when R is significantly less risky or not too costly compared to U, then the buyer's optimal strategy is to select R. As the cost differential increases or risk differential decreases, the buyer's optimal decision changes, and he must then sole source from U. Subsequently, we utilize an experimental approach with performance-based payment for subjects who act as buyers and compare the results to the theoretical benchmark. Our experimental setup closely follows the theoretical one and focuses on six scenarios generated by combining the following: (i) low and high cost differentials and (ii) low, medium, and high reliability differentials between the two suppliers. Our examination of these various settings enables us to answer the following questions.

- How does the procurement strategy of the subjects compare to the theoretical optimal? What is the impact of the deviations, if any, from the theoretical optimal on the profits of the buyer?
- What behavior on the part of the subjects explains the observed deviations?
- How robust are the above results as it pertains to the experimental settings (e.g., paid versus unpaid subjects) or measurement techniques?

Comparison of the experimental findings to the theoretical solution reveals several insights.

First, the procurement strategy of the subjects differs significantly from the theoretical optimal. Specifically, in contrast to the theoretical model, subjects *overwhelmingly opt for dual sourcing*, i.e., order from both U and R. Subjects in our settings, on average, never allocate more than 61% to U or more than 74% to R. Interestingly, although subjects do not perform well when seen from the above perspective, they seem to be quite capable of accounting for the effects of cost and reliability differentials in their decision making. Specifically, in line with the theoretical model, as the cost differential between the two suppliers increases or the reliability differential decreases, they allocate a higher proportion of the order to U, and vice versa. The nonoptimal ordering decisions by the subjects can result in significant profit penalty for the buyer ranging in our experimental settings from approximately 9% to 21%.

In addition to documenting the deviation from optimality, we also discuss why subjects exhibit the above behavior, which cannot necessarily be explained by a risk-minimization approach. Particularly, when the theoretical optimal is to order only from R, diversification results in the subjects actually injecting risk into a system when the optimal decision is risk free. Our analysis suggests *bounded rationality* on the part of the subjects as a possible rationale. Indeed, subjects exhibit significant amount of bounded rationality in all the six experimental settings. Furthermore, subjects are more boundedly rational when theoretically the order should go solely to the lower cost but risky supplier U, rather than when the optimal selection is the more expensive supplier R. Last, the above insights do not appear to be artifacts of our assumptions. Indeed, they remain qualitatively valid irrespective of whether or not: (i) the subjects are paid, (ii) they have previous exposure to possible benefits of diversification (e.g., through courses in finance), and (iii) we allow subjects time to gain experience about the experimental setup. Our results also hold true even if we change certain measurement approaches, e.g., how we quantify the extent of diversification or whether we use averages or medians for statistical testing.

2. Related Literature

For a number of years, research in OM has focused on building analytical and empirical models to analyze decisions made in operational settings. More recently, there has been considerable attention on decision-making behavior of managers in practice, especially when the theoretical structure of the problems is complex and the analytical solutions are not easy to implement. Two major areas of interest have emerged in the behavioral OM literature: studying stocking decisions in the newsvendor setting because it serves as a well-understood archetype of stochastic inventory problems, and analyzing the causes and effects of uncoordinated supply chains. We offer a brief review of the first stream, which is more related to our research. For the second stream we refer readers to Croson and Donohue (2006), Loch and Wu (2008), Katok and Wu (2009), Bendoly et al. (2010), and Kalkanci et al. (2011).

The newsvendor problem has served as a cornerstone for the behavioral operations literature because of the problem's focus on managing overstocking and understocking risks, which are the primary drivers of many operational decisions. Whereas it is optimal to make a stocking decision that balances these two risks, Schweitzer and Cachon (2000) find that orders by experimental subjects show significant anchoring around the mean of the demand distribution. In a refinement, Ben-Zion et al. (2008) show that subjects show learning behavior and their order sizes are between the mean demand and the quantity that maximizes the expected profit. As shown by Bolton and Katok (2008), better decisions can be facilitated through experience and feedback as deliberate learning softens the anchoring effect around mean demand. Providing feedback with excessive frequency, however, can lead to undue focus on recent events and results in a performance decline (Lurie and Swaminathan 2009). These and other papers (for a recent review, see Becker-Peth et al. 2013) have made significant contributions to improving our understanding of how managers actually match supply and demand under demand uncertainty.

There is also a significant and growing body of theoretical and empirical papers dealing with supply risk management that is closely related to our research. In particular, the paper by Dada et al. (2007) offers theoretical underpinnings for our experimental research. In their paper, the authors study the newsvendor problem with multiple unreliable suppliers and determine the optimal order allocation strategy when suppliers differ in terms of both costs and reliabilities. This and other such papers offer a robust theoretical framework for supply risk management under a variety of settings (e.g., see Gurnani et al. 2000, Tomlin 2009, Yu et al. 2009, Yang et al. 2009, Sodhi et al. 2012, and references therein). There are also a number of data- or survey-based empirical papers that investigate related issues from a number of perspectives. For example, Wagner and Bode (2008) and Hendricks and Singhal (2005) discuss the different types of possible supply risks and their effects on supply chain performance, Braunscheidel and Suresh (2009) investigate the factors that can most effectively help a supply chain deal with such risks by increasing its agility, whereas Jiang et al. (2009) focus on understanding the causes and effects of labor-related supply risks. The few behavioral papers that exist in this stream primarily focus on how managers perceive risk, not necessarily disruption type, at different levels of organizations and how it affects business strategy including purchasing (e.g., Kraljic 1983, Stone et al. 1994, Harrison et al. 2009, Smith 2009, Puljic 2010). Among the papers that deal specifically with supply disruption risk, Zsidisin (2003) uses case studies to define such risk and illustrate how it can negatively affect business operations, whereas Ellis et al. (2010) use survey to address how managers perceive the probability and magnitude of disruption risk in their search for alternative source of supply. However, experimental investigation of the order allocation decision between asymmetric suppliers (in terms of costs and risks), the focus of this paper, remains relatively less explored in the extant literature.

Our findings reveal the use of a diversification strategy that leads to nonoptimal order splitting. The prevalence of such a diversification bias—when it is not optimal to diversify—has been observed previously in consumption and investment decisions. Diversification in (simultaneous) consumption decisions was first demonstrated by Simonson (1990) and later in investment settings by Benartzi and Thaler (2001). Read and Loewenstein (1995) dub this phenomenon *diversification bias*, and Thaler (1999) explains it as a manifestation of the mental accounting's effect on ex ante cost–benefit analysis (for more details, refer to Fox et al. 2005). We demonstrate that procurement decisions in the face of supply uncertainty can also be subject to diversification bias and quantify the possible impact of such bias on the profit performance of the firm. Furthermore, we show that bounded rationality offers an explanation for this phenomenon in our case. Thus, we complement works such as Ho and Zhang (2008) and Su (2008), which have studied the impact of bounded rationality in other operational settings.

Behavioral decision making is clearly an important and growing area of research in operations management. Our contribution to this body of work is fourfold. We first demonstrate a systematic diversification in procurement-related decision making in contrast to the sole-sourcing theoretical outcome and measure the impact of such diversification on the expected profits for the buyer under certain conditions. Second, we analyze the subjects' understanding of cost and capability differentials between the suppliers and its effect on the order allocation decision. Third, we show that the above results are quite robust with respect to the experimental settings and measurement techniques. Finally, we discuss bounded rationality as a possible rationale for the above behavior of subjects.

The rest of this paper is organized as follows. We first develop several testable hypotheses based on a theoretical model in §3. Subsequently, we discuss the experimental design and the results from the experiments in §4. The bounded rationality model is discussed in §5, and §6 checks the robustness of the results. The concluding discussion is provided in §7.

3. Theoretical Model and Hypotheses

In this section, we develop a theoretical model of a buyer who is procuring a particular product from two heterogeneous suppliers who are different in terms of their costs and reliabilities. To focus on the issue of supply risk, suppose that the end-customer price and demand for the product are constant (denoted by p and D, respectively). The buyer needs to satisfy this demand by procuring from suppliers U and R. Any inventory excess to the requirement is worthless to the buyer, whereas any unmet demand results only in the loss of potential revenue p per unit.

Regarding the two suppliers, it costs c_u and c_r for each unit procured from U and R, respectively, where $c_u \le c_r < p$. However, the cheaper supply source U is also less reliable. Specifically, only supplier U faces supply risk, whereas supplier R is fully reliable in terms of delivering her order. In our setting, U faces two types of risks: a *disruption risk*, because of which (with probability p_d) the whole order allocated to this supplier will not be available for use by the buyer, and a *yield risk* because of which, even when there is no disruption, only a random fraction of the order (denoted by α) is delivered to the buyer. We assume that the yield factor α is a positive random variable with distribution F and density f. Conversely, R faces neither disruption nor yield risk.

The objective of the buyer is to decide how much to order from each supplier so as to maximize his profit. Suppose that the nonnegative order quantities from U and R are q_u and q_r, respectively. Given the above conditions, we can show that the buyer's expected profit function is given by

$$\Pi(q_u, q_r) = pD - p_d[c_r q_r + p(D - q_r)] - (1 - p_d)\left[c_r q_r + c_u q_u E(\alpha) + p\int_0^{(D-q_r)/q_u} (D - \alpha q_u - q_r) f(\alpha)\, d\alpha\right],$$

where E is the expectation operator; that is, the buyer needs to maximize Π by selecting the optimal q_u and q_r. Since the buyer faces a deterministic demand D, clearly $q_r \le D$. Analyzing the profit function, we can establish the following. (The proof is provided in the online supplement, available at http://dx.doi.org/10.1287/msom.2013.0453.)

Proposition 1. *The optimal procurement strategy for the buyer is sole sourcing. There exists a unique $\hat{p}_d$ such that if $p_d < \hat{p}_d$, then the buyer procures only from U, and if $p_d \ge \hat{p}_d$, then he procures only from R.*

Specifically, if U is uniformly distributed in $[\frac{1}{2}, 1]$, then $\hat{p}_d = ((c_r + p)\sqrt{p} - p\sqrt{p + 3c_u})/(2p\sqrt{p} - p\sqrt{p + 3c_u})$. In that case,

(i) *if $p_d < \hat{p}_d$, the buyer's optimal order allocation is $q_u^* = 2D\sqrt{p/(p + 3c_u)}$ and $q_r^* = 0$;*

(ii) *if $p_d \ge \hat{p}_d$, the buyer's optimal* order *allocation is $q_r^* = D$ and $q_u^* = 0$.*

The optimal profit for the buyer can be obtained by substituting $q_u = q_u^*$ and $q_r = q_r^*$ in the buyer's expected profit function Π.

Clearly, if U is not too unreliable in terms of disruption risk (i.e., if p_d is not too high), then the optimal strategy for the buyer is to choose U; otherwise, he chooses R. Note that the threshold disruption risk level $\hat{p}_d$ is a function of system parameters. Analyzing that threshold value we can deduce that $\hat{p}_d$ is decreasing in c_u and increasing in c_r; that is, as the disruption risk of the unreliable supplier U decreases (i.e., as the reliability differential between the two suppliers decreases), it becomes more likely that the whole order will be allocated only to U. On the other hand, as the marginal cost of U increases or that of the reliable supplier R decreases (i.e., as the cost differential between the two suppliers decreases), it becomes more likely that the whole order will be allocated only to R.

Based on the above theoretical model, we can then propose the following hypotheses about the optimal procurement strategy for the buyer.

Hypothesis 1 (Sole Sourcing). *When allocating order between suppliers U and R, the buyer will opt for sole sourcing, i.e., allocate the entire order to either U or R.*

Hypothesis 2 (Sensitivity of Ordering Decision). (a) Cost Differential. *As the cost differential between suppliers U and R decreases, a larger proportion of the buyer's order will be allocated to R.* (b) Reliability Differential. *As the reliability differential between suppliers U and R decreases, a larger proportion of the buyer's order will be allocated to U.*

Our objective in this paper is to test the above hypotheses through experiments and determine whether real-life subjects follow the above strategy and, if not, document the extent and cause of their deviations.

4. Experimental Design and Results

4.1. Experimental Design

In this section, we describe the experimental design that we use to test the hypotheses of §3. Our experimental setting closely follows the theoretical model described above. The objective for the subjects is to act as the buyer and choose order quantities for a particular product from two suppliers with differing costs and risks (like U and R) with the aim of maximizing profit. We make the following common assumptions about the product throughout the experiments: (i) the end-customer selling price is $p = \$45$ per unit, (ii) the end-customer demand is known to be $D = 100$ units, (iii) any leftover unit has no salvage value, and (iv) any unsatisfied demand only results in lost revenue (i.e., \$45 per unit) for the buyer. One of the suppliers is reliable (R) and can always deliver the exact amount of units requested from her and charges $c_r = \$30$ per unit. The other supplier, U, is cheaper, but faces disruption and yield risks. In all our experiments, if U's supply is not disrupted, her yield is assumed to be uniformly distributed between 0.5 and 1; i.e., if, for example, 80 units are ordered from U and the yield realization is 0.75, the buyer will only receive 60 units. Conversely, if there is a disruption, there will be no supply from U.

We then generate six experimental settings. They differ in terms of cost and reliability differentials between the two suppliers, based on two levels of marginal cost c_u charged by U for each delivered unit and three levels of probability of supply disruption faced by U (i.e., p_d). Specifically:

- *Cost Differences*. In three of the six of the settings, the marginal cost for U is assumed to be $c_u = \$18$ per delivered unit, which we refer to as the low-cost (LC) setting. In the remaining three high-cost (HC) settings, $c_u = \$23$ per delivered unit. Note that the LC setting (respectively, HC setting) represents a high (respectively, low) cost differential between the suppliers.
- *Reliability Differences*. For each cost setting, we ran three experiments with the following probabilities of supply disruption p_d: zero probability of disruption (ZP) = 0, low probability of disruption (LP) = 0.2, and high probability of disruption (HP) = 0.5. Clearly, ZP, LP, and HP represent zero, low, and high reliability differentials between the suppliers, respectively.

The above scenarios give rise to the six settings showed in Table 1. The table also shows the optimal theoretical order quantities for each setting based on our analysis in the last section.

A total of 204 business students from a large public university participated in the experiments. Subjects were recruited through a computerized pool and randomly presented with one of the six settings during separate time windows. There were at least 32 subjects in each setting, and each subject participated in only one setting. Subjects who participated received *performance-based monetary compensation* in two parts. Specifically, each subject received \$6 for participating in the experiment and also a payment ranging from \$6 to \$14 based on their profit performance in the experiments. The higher the profit (i.e., closer it is to the theoretical optimal), the larger the second part of the compensation. The average compensation was approximately \$16 per participant. In each setting, subjects were asked to decide how many units they wanted to order from each supplier. To ensure that the sequence of decision making did not affect the findings, half of the subjects were asked to fill out the order quantities from the unreliable supplier first, and the remaining half had the reliable supplier first. The problem was clearly explained to the subjects through a welcome screen that described the costs and risks involved (refer to Figure A.1 in Appendix A for a screenshot). In all settings, 30 rounds of the problem were presented to the subjects. In each round, after subjects decided their orders from each supplier, they were shown the actual delivered quantities, which depended on whether the unreliable supplier's supply was disrupted or not. The profits from the previous order were also shown at the end of each round. Subjects were told that their performance would be judged based on the average profits they earn during the 30 rounds. At the end of the session, subjects were also asked to describe their thought process in a few words so that subjects who did not show any understanding of the problem could be removed from the final sample.

Table 1 Optimal Order Quantities in the Six Experimental Settings

	$c_u = \$18$ (LC)	$c_u = \$23$ (HC)
$p_d = 0$ (ZP)	$q_u^* = 134.8$, $q_r^* = 0$	$q_u^* = 125.7$, $q_r^* = 0$
$p_d = 0.2$ (LP)	$q_u^* = 134.8$, $q_r^* = 0$	$q_u^* = 0$, $q_r^* = 100$
$p_d = 0.5$ (HP)	$q_u^* = 0$, $q_r^* = 100$	$q_u^* = 0$, $q_r^* = 100$

4.2. Results

The results of the experiments are provided in Table 2, which shows the average order quantities from the two sources, i.e., (q_u, q_r), and the number of subjects (n) in each of the six settings. We also include the corresponding theoretical optimals for each of the settings. In this section, we will first compare the theoretical and experimental values to test the hypotheses of §3 and characterize the ordering deviations of subjects, if any, from optimality. Then, we will also discuss certain salient ordering behavior of the subjects that can be gleaned from the data.

4.2.1. Hypothesis 1: Sole-Sourcing Hypothesis. First, we note that the actual ordering quantities differ from the theoretical prediction. Recall that it is

Table 2 Experimental and Theoretical Order Quantities

	$c_u = \$18$ (LC)	$c_u = \$23$ (HC)
$p_d = 0$ (ZP)	$q_u = 70.7$, $q_r = 44.0$, $n = 32$ ($q_u^* = 134.8$, $q_r^* = 0$)	$q_u = 57.5$, $q_r = 54.7$, $n = 34$ ($q_u^* = 122.2$, $q_r^* = 0$)
$p_d = 0.2$ (LP)	$q_u = 45.1$, $q_r = 62.1$, $n = 37$ ($q_u^* = 134.8$, $q_r^* = 0$)	$q_u = 35.4$, $q_r = 74.4$, $n = 32$ ($q_u^* = 0$, $q_r^* = 100$)
$p_d = 0.5$ (HP)	$q_u = 33.3$, $q_r = 80.4$, $n = 35$ ($q_u^* = 0$, $q_r^* = 100$)	$q_u = 26.8$, $q_r = 77.6$, $n = 34$ ($q_u^* = 0$, $q_r^* = 100$)

optimal to not order any units from the reliable supplier R in the LCZP, LCLP, and HCZP cases, and it is optimal to not order any units from the unreliable supplier U in the other three cases. Yet, in the experiment, subjects place orders that deviate from this optimal policy by ordering from both suppliers in all the six settings.

To study this deviation systematically, we introduce a new measure termed the *diversification ratio* (DR). Specifically, we define the *average diversification ratio* of all subjects under a particular experimental setting as

$$\mathrm{DR}_E = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{t=1}^{30} q_{uit}}{\sum_{t=1}^{30}(q_{uit}+q_{rit})}\right), \tag{1}$$

where n represents the number of subjects participating in that particular setting, and q_{uit} (respectively, q_{rit}) represents the order placed by subject i in round t with supplier U (respectively, supplier R). In our study, the diversification ratio is especially valuable to detect behavioral deviations because the theoretical diversification ratio is either 0 or 1 in all settings. Note that the theoretical value of diversification ratio is calculated in each setting as $\mathrm{DR}_T = q_u^*/(q_u^* + q_r^*)$, where q_u^* and q_r^* are the theoretically optimal quantities from suppliers U and R, respectively. We then compare DR_E and DR_T for each of the six settings in Table 3, which also shows the t-statistic for our hypothesis that $\mathrm{DR}_E = \mathrm{DR}_T$.

Subjects do not sole source. The data strongly suggest that subjects do not follow the theoretically optimal strategy of exclusive sole sourcing. In all six settings, *subjects diversify by placing orders from both suppliers*. (In all settings, $t(n) \geq 6.81$ and $p < 0.001$.) In other words, regardless of the setting, the subjects dual source, and the diversification ratios are significantly different from 0 or 1, whichever is optimal. This establishes that Hypothesis 1 is *not* supported by our experiments.

Note that in the three settings in which $\mathrm{DR}_T = 1$, the tendency of subjects to allocate some of the demand to the reliable supplier can perhaps be explained by risk aversion. However, in the settings in which $\mathrm{DR}_T = 0$, risk aversion does not explain diversification. Indeed, because it is optimal even for a risk-neutral buyer to sole source from the reliable supplier, a risk-averse subject should also avoid sourcing from the unreliable supplier. However, we find that DR_E is significantly different from 0 in the LCHP, HCLP, and HCHP conditions (with $t(35) = 6.81$, $t(32) = 7.94$, and $t(34) = 7.61$, respectively). This behavior is not consistent with risk aversion (which would imply that subjects should prefer the risk-free reliable supplier rather than the gamble of the risky unreliable one).

It is no surprise that subjects, on average, do not order the optimal quantities from the two suppliers in light of their failure to source exclusively from the optimal source as is evident from Table 2. Clearly, subjects neither order D from the reliable supplier nor order q_u^* from the unreliable one.

As an alternative method of characterizing the deviation from optimality due to diversification, we calculate the frequency with which subjects choose order quantities that are close to the theoretical optimal levels. In this context, we first consider an order quantity (q_u or q_r) within 10 units of the theoretical solution (q_u^* or q_r^*, respectively) as a "near-optimal" decision by the subject. Interestingly, we find that across the six experimental settings, subjects, on the average, place near-optimal q_u and q_r orders in only 24.3% and 32.2% of instances, respectively. Details for the different settings are provided in Table 4. Subsequently, we also calculated the frequency with which subjects choose "near-conditionally optimal" order quantities, that is, given a q_u (respectively, q_r) chosen by a subject, how frequently (s)he chooses an order quantity within 10 units of the corresponding conditionally optimal order value $(q_r^* \mid q_u)$ (respectively, $(q_u^* \mid q_r)$). As shown in Table 4, even in that case the performance is rather poor.

Finally, we also considered whether subjects use the naive diversification strategy suggested by Benartzi and Thaler (2001). Since we have two suppliers, as per Benartzi and Thaler (2001) we would expect most of the subjects to split their orders equally between them. However, it turns out that our subjects generally do not follow this strategy. Specifically, on average, they place approximately same sized orders (i.e., within 10 units of each other) only in 11.75% of all

Table 3 **Experimental and Theoretical Diversification Ratios**

	$c_u = \$18$ (LC)	$c_u = \$23$ (HC)
$p_d = 0$ (ZP)	$\mathrm{DR}_T = 1$, $\mathrm{DR}_E = 0.595$, $n = 32$; $t(n) = 8.37$	$\mathrm{DR}_T = 1$, $\mathrm{DR}_E = 0.499$, $n = 34$; $t(n) = 12.57$
$p_d = 0.2$ (LP)	$\mathrm{DR}_T = 1$, $\mathrm{DR}_E = 0.410$, $n = 37$; $t(n) = 15.47$	$\mathrm{DR}_T = 0$, $\mathrm{DR}_E = 0.311$, $n = 32$; $t(n) = 7.94$
$p_d = 0.5$ (HP)	$\mathrm{DR}_T = 0$, $\mathrm{DR}_E = 0.257$, $n = 35$; $t(n) = 6.81$	$\mathrm{DR}_T = 0$, $\mathrm{DR}_E = 0.249$, $n = 34$; $t(n) = 7.61$

Table 4 **Fraction of Near-Optimal Orders (Orders Within 10 Units of the Theoretical Solution)**

	Near optimal (%)		Near conditionally optimal (%)	
Setting	q_u	q_r	q_u	q_r
LCZP	4.52	21.40	9.78	15.59
LCLP	1.57	12.35	8.92	12.55
LCHP	36.53	46.53	6.80	5.07
HCZP	9.12	14.80	10.39	16.67
HCLP	45.11	46.22	8.22	14.11
HCHP	49.19	52.02	5.56	5.56

decisions. So, their diversification strategy is perhaps more nuanced. This underscores the need to understand whether subjects are internalizing the basic trade-off between cost and reliability, and whether they understand the implications of their ordering decisions.

4.2.2. Hypotheses 2(a) and 2(b): Sensitivity Hypotheses. Although subjects clearly exhibit a tendency to utilize both sources, Hypotheses 2(a) and 2(b) of §3 suggest that if they understand the basic trade-off, they should at least increase the allocation to the reliable supplier if there is an increase in the cost or disruption probability of the unreliable supplier. We test these through several pairwise comparisons of ordering decisions.

Cost Differential Effect. We know from §3 that, given a particular reliability differential, as the cost of the unreliable supplier increases (relative to the reliable supplier), the diversification ratio DR_E should decrease. In our experiment, for both ZP conditions, $DR_T = 1$ is optimal because of the high reliability of supplier U, and in both HP conditions, $DR_T = 0$ is the optimal strategy. On the other hand, in the LP conditions, the optimal strategy switches from $DR_T = 1$ to $DR_T = 0$ as the cost of the unreliable supplier increases. In Figure 1, the observed pair of diversification ratios for low- and high-cost settings are shown for each disruption probability condition (i.e., p_d). For ZP and LP conditions, we find the diversification ratios in the low-cost setting are significantly higher than those in the corresponding high-cost setting ($p < 0.1$ and $p < 0.05$, respectively); for the HP condition, the difference under the two cost settings is not significant. Therefore, Hypothesis 2(a) is partially supported. Interestingly, subjects are sensitive to cost difference particularly when the reliability difference between the suppliers is lower (ZP and LP cases). This suggests that subjects use cost as a differentiating aspect between suppliers especially when reliability differences are minimal.

Reliability Differential Effect. The order quantities q_u, q_r for various disruption probability settings are given in Figure 2. For a given cost differential, as the reliability differential between the two suppliers increases, we theoretically expect the diversification ratios to decrease, i.e., more order should be allocated to the reliable supplier R. Note that the theoretical diversification ratios DR_T for the two different cost settings are as follows: For low-cost settings, $DR_T = 1, 1$, and 0 for LCZP, LCLP, and LCHP settings, respectively; for high-cost settings, $DR_T = 1, 0$, and 0 for HCZP, HCLP, and HCHP settings, respectively.

For each cost setting, we find that the average observed diversification ratio (DR_E) is, in general, significantly decreasing with the probability of disruption p_d. Specifically, it holds true for the low-cost setting (at least $p < 0.05$); for the high-cost setting, $DR_{E,\,HCZP} > DR_{E,\,HCLP}$ and $DR_{E,\,HCZP} > DR_{E,\,HCHP}$ ($p < 0.001$ and $p < 0.05$, respectively), but $DR_{E,\,HCLP}$ is not significantly different from $DR_{E,\,HCHP}$. This implies that subjects, in general, allocate a larger proportion of the order to the unreliable supplier U as the reliability differential decreases, providing (partial) support for Hypothesis 2(b).

The support for the above hypotheses establishes that subjects tend to diversify significantly more than

Figure 1 **Effect of Cost Differential on Diversification Ratios**

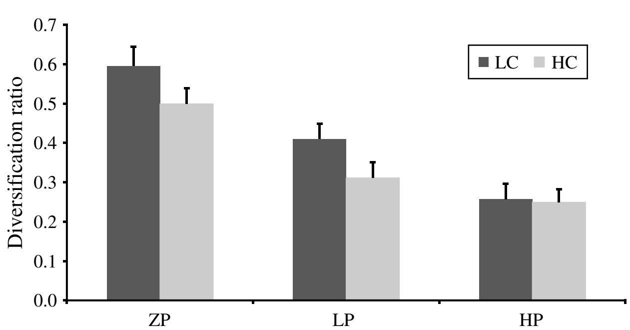
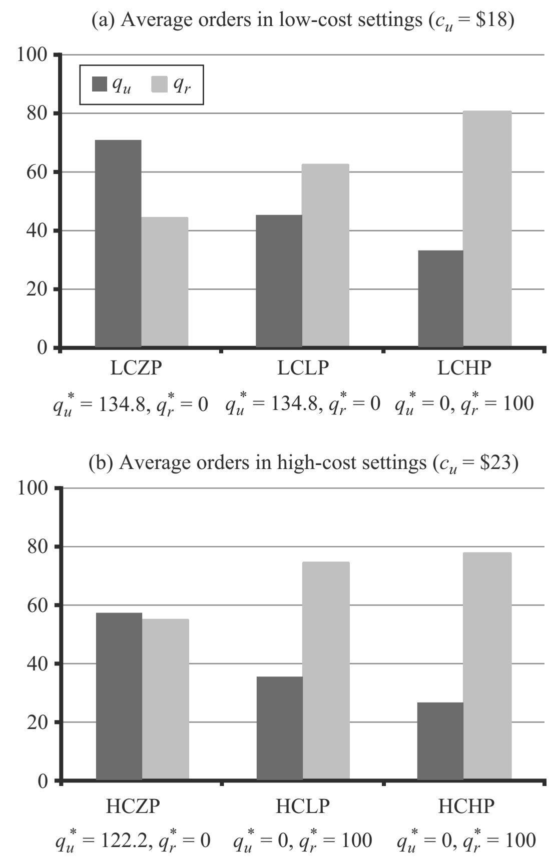


Figure 2 **Experimental Order Quantities for Different Probability Levels**



what is theoretically necessary, but react appropriately (albeit insufficiently) to any change in the cost or riskiness of the suppliers. The latter point is also supported by the fact that in all of the three cells where the subjects decide to partly use the reliable supplier R (respectively, risky supplier U) rather than the optimal strategy of using only supplier U (respectively, supplier R), their total order sizes $(q_u + q_r)$ are smaller than the optimal order size of q_u^* (respectively, q_r^*) to account for the higher (respectively, lower) reliability in the supplier base.

4.2.3. Ordering Characteristics. Motivated by the behavioral OM literature in newsvendor setting, we now report certain salient ordering behavior of the subjects in our setting.

Supply Chasing. First, we investigate whether subjects (within a setting) modify orders based on the performance of the unreliable supplier in the previous round. For example, subjects could employ a *supply chasing* heuristic, which would be similar to the demand chasing behavior proposed by Schweitzer and Cachon (2000) in a newsvendor setting. This would imply that subjects will redirect orders away from the unreliable supplier to the reliable one following periods of disruption. We compare the average order values in periods following *disruptions* (q_u^A and q_r^A) with the overall averages in Table 5. Interestingly, the differences between them are *not* statistically significant in any of the four settings (LCZP and HCZP have no disruptions). To understand this, we parsed through the verbal answers given by subjects to an open-ended question asking them to describe their sourcing strategies. Most subjects describe an attempt to find a comfortable balance between the two suppliers, with only minor tweaks to the strategy once it is developed. Some subjects do follow a process similar to supply chasing. But this is counterbalanced by some others actually increasing orders from the unreliable supplier *after* rounds with disruptions, perhaps assuming the probability of consecutive bad events to be minimal (i.e., they are perhaps not recognizing that events in different periods are independent).

Anchoring. Behavioral research on newsvendor decision making also suggests that, facing demand uncertainty, subjects anchor their order quantities in the experimental setup to the average demand (Schweitzer and Cachon 2000, Bolton and Katok 2008, Gavirneni and Xia 2009). In contrast to these prior works, demand in our experiment is deterministic (100 units), but subjects face uncertain supply. Paralleling these prior works, we test whether subjects have a tendency to match expected supply and demand, when supply is unreliable. As noted in the theoretical-model-based Table 1, the optimal order size depends on the random yield distribution (and not on the probability of disruption) once the supplier selection decision is made. Considering the expectation of the random yield distribution only, the expected number of units received corresponding to the orders placed by subjects in each setting equals $(q_r + 0.75 * q_u)$ and is given in Table 6. We find that the anchoring prediction is strongly supported by the data. As shown in the table, in five of the six experimental settings, the expected number of delivered units is *not* significantly different from the demand of 100 units. The only setting in which the two are significantly different at the 5% level is the LCLP case. The difference is also weakly significant (at 10%) in the HCZP setting. Even in these two settings, the subjects place orders such that the average number of delivered units is within 5% of the deterministic demand of 100 units. Therefore, in general, subjects appear to anchor their ordering decisions around points at which the expected supply matches demand. It is worth noting that we find this support for the anchoring heuristic in spite of the fact that individual subjects are making vastly different decisions regarding how these orders are being allocated between suppliers in each round of the experiment.

Table 5 Average Orders After Disruptions Compared to the Overall Average

Setting	q_u^A	q_r^A	$\bar{q}_u$	$\bar{q}_r$	$q_u^A - \bar{q}_u$	$q_r^A - \bar{q}_r$
LCLP	46.8	61.0	45.1	62.1	1.71	−1.02
LCHP	32.3	81.3	33.3	80.4	−1.02	0.92
HCLP	36.8	71.9	35.4	74.4	1.45	−2.52
HCHP	24.3	79.4	26.8	77.6	−2.55	1.82

Table 6 Expected Number of Delivered Units

Setting	Demand	$q_r + 0.75 * q_u$	p
LCZP	100	97.0	0.202
LCLP	100	95.9	0.022
LCHP	100	105.3	0.181
HCZP	100	97.8	0.070
HCLP	100	100.9	0.633
HCHP	100	97.7	0.196

4.2.4. Impact of Allocation Decision on Profits. Until now we have focused on the nature of ordering decisions made by subjects in our experimental settings and showed a systematic deviation from optimality in the form of order diversification. This obviously raises the issue as to what are the implications of this behavior on the profits obtained. We define the following new metric to quantify this impact.

Average Profit Deviation. Our objective is to compare the average profits obtained by subjects with their actual orders to the expected profit that could have been obtained had they ordered the optimal quantities from the suppliers. The average profits obtained by subjects in a particular setting are simply

$$\pi^E = \frac{\sum_{i=1}^{n}\sum_{t=1}^{30}\pi_{it}}{30n},$$

where π_{it} represents the expected profit corresponding to the orders placed by subject i in round t of the experiment, and n is the number of subjects in the setting. Similar to the diversification ratio, we now calculate the average profit deviation for each setting as

$$\Delta\pi = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\sum_{t=1}^{30}\pi_{it}}{30\pi^*}\right) = 1 - \frac{\pi^E}{\pi^*},$$

where π^* represents the optimal expected profit.

In Table 7, for each setting, we show the optimal expected profits (π^*), the average profits obtained by subjects in the experiments (π^E), the associated average profit deviation ($\Delta\pi^* = (\pi^* - \pi^E)/\pi^*$), and the ranking of the deviation (1 representing the highest deviation and 6 the lowest). The profit impact of subjects deviating from the optimal orders ranges from 9% to 21% in various settings; moreover, all of these differences are statistically significant ($p < 0.01$ for all six settings). Interestingly, the highest average profit deviation is observed in the LCZP setting ($\Delta\pi^* = 21.15\%$), although we know from Table 3 that the diversification ratio in this setting is not the worst (relative to the optimum) among all settings. Similarly, the HCLP setting, where the smallest profit deviation is observed ($\Delta\pi^* = 8.85\%$), does not represent the best order quantity selection by the subjects. Comparing the profit impact of ordering decisions across different settings, we observe that the impact of diversification is especially stronger in the settings in which sole sourcing from the unreliable supplier is optimal (i.e., $\mathrm{DR}_T = 1$; LCZP, LCLP, and HCZP settings). Specifically, diversification leads to an average profit reduction of 18.9% in these cells, but the average profit reduction is only 10.78% in the remaining three cells where it is optimal to source exclusively from the reliable supplier (i.e., $\mathrm{DR}_T = 0$; LCHP, HCLP, and HCHP settings).

Table 7 **Expected Profits from Theory and Experiments**

Setting	π^*	π^E	$\Delta\pi^*$ (%)	Profit impact rank
LCZP	2,325.42	1,833.71	21.15	1
LCLP	1,860.34	1,472.21	20.86	2
LCHP	1,500.00	1,354.46	9.70	5
HCZP	1,837.60	1,567.78	14.68	3
HCLP	1,500.00	1,367.25	8.85	6
HCHP	1,500.00	1,292.91	13.81	4

5. Bounded Rationality Model: Theory and Estimation

Whereas it is important to point out the above tendency of diversification in procurement (as well as its extent and impact), a related research issue then is to understand what explains the observed deviations. As discussed before in §4.2, risk aversion is not able to do so in our setting. Note that loss aversion and regret aversion are also not able to explain the phenomenon, since they too theoretically predict sole sourcing as the optimal strategy. (We do not go into the details of this assertion due to space constraints.) However, in this section, we develop a model of boundedly rational decision making in the context of our procurement problem that is indeed able to provide a plausible reason as to why the subjects are opting for the diversification strategy.

Following recent works such as Su (2008) and Ho and Zhang (2008), we consider a quantal choice model that allows random errors in decision making. The salient aspects of such a model are as follows: (a) individuals do not always pick the optimal alternative; (b) they consider all available options; (c) however, they are more likely to choose better options than worse ones. The probability of a particular decision i in such a choice model is proportional to some (nondecreasing) function of the utility obtained from that decision, u_i. Within this framework, a common approach to modeling the variation in subjects' decisions is the logit choice model, wherein the probability of selecting i is proportional to e^{u_i}. To model bounded rationality, the logit choice probability of selecting choice i may be written (for a continuous decision domain) as

$$\psi(x_i) = \frac{e^{u(x_i)/\beta}}{\int_x e^{u(x_i)/\beta}}, \tag{2}$$

where β is the bounded rationality parameter. Note that $\beta = 0$ represents a scenario where decision makers are perfectly rational and always select the utility maximizing choice (or one of the utility-maximizing choices if there are several). On the other extreme, $\beta \to \infty$ represents a situation where decision makers are randomly choosing alternatives with no motivation or ability to optimize; $\psi(\cdot)$ devolves into a uniform distribution in this case. We refer to Anderson et al. (1992) for more information about the logit choice model, and Su (2008) for a more recent and thorough discussion.

5.1. Theory

Unlike prior models on bounded rationality in operations management that have involved a single decision, subjects in our experiments need to utilize a two-dimensional decision setup. However, the discrete choice model of bounded rationality can still be used because only the expected utilities of various choices matter. We first describe the application of the logit choice model to our experimental setting.

Suppose that a particular combination of order quantities from the reliable and unreliable suppliers, $x_i = \{q_{ri}, q_{ui}\}$, yields an expected profit of $f(x_i)$. Assuming a linear utility function and using $f(x_i)$ as a substitute for $u(f(x_i))$ (similar to Ho and Zhang 2008), for a given bounded rationality parameter β, the logit choice probabilities of each combination may be written as

$$\psi(x_i) = \frac{e^{f(x_i)/\beta}}{\int_{q_{ui}=0}^{\infty}\int_{q_{ri}=0}^{\infty} e^{f(x_i)/\beta}}. \tag{3}$$

The denominator may be imagined as the volume under the surface of the expected profit function (we have a two-dimensional decision space), with the shape of the surface itself depending on the parameter β. Therefore, we represent the denominator with $V_\beta = \int_{q_{ui}=0}^{\infty}\int_{q_{ri}=0}^{\infty} e^{f(x_i)/\beta}$. If subjects in the experiment are highly rational with β close to 0, a vast majority of their responses will be concentrated at or near the theoretically optimal combination of q_u and q_r (i.e., q_u^* and q_r^*). For higher levels of β, the responses will be more dispersed. The expected distributions of responses as a function of the bounded rationality parameter β are illustrated in Figure 3.

Suppose there are N observations in a particular experimental setting: $x_1, x_2, \ldots, x_N$. The joint likelihood of obtaining this combination is as follows (Casella and Berger 2001):

$$L(x_1, x_2, \ldots, x_N \mid \beta) = \frac{\Pi_{k=1}^{N}(e^{f(x_k)/\beta})}{V_\beta^N}. \tag{4}$$

As a measure of the bounded rationality in this setting, we will find the β that maximizes (4). Equivalently, we can focus on the joint log-likelihood of

$$LL(\beta) = \Sigma_{k=1}^{N}\frac{f(x_k)}{\beta} - N\log(V_\beta). \tag{5}$$

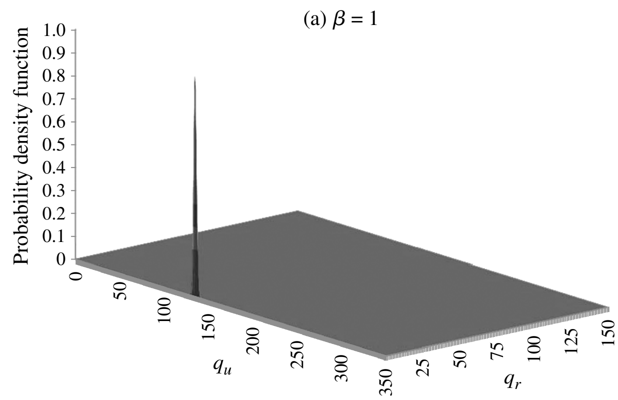
We will use β^* to denote the argument that maximizes the log-likelihood function $LL(\beta)$ in (5).

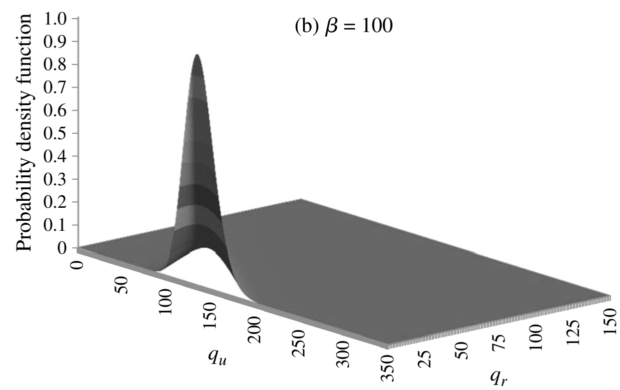
5.2. Estimations

The maximum likelihood estimates (MLEs) of the bounded rationality parameter β^* are presented in Table 8 for the six settings of our framework. The MLEs (β^*) are significantly larger than 0 for all of them, *indicating that the evidence of bounded rationality is strongly present in all six experimental settings*. The log-likelihood values of an arbitrarily small β are also given for comparison purposes. It is possible to consider a likelihood ratio test to consider the hypothesis that β is arbitrarily close to 0. Conservatively, a test statistic may be computed as $\chi^2 = 2 * (LL(\beta^*) - (LL(\beta = 1)))$. With 1 degree of freedom, the critical value of $\chi^2(0.99) = 6.635$, which is exceeded comfortably in each setting. Therefore, bounded rationality's role in the decisions we observe is strongly significant in all six settings.

As we show in Figure 3, a larger value of β distributes responses away from the optimal combination. An important consequence of this dispersion is the deviation from the sole-sourcing strategy. Indeed, for larger values of β, the majority of responses that have the same probability of occurrence do not result in sole sourcing. In other words, the diversification

Figure 3 Response Distribution and Bounded Rationality for the LCZP Setting





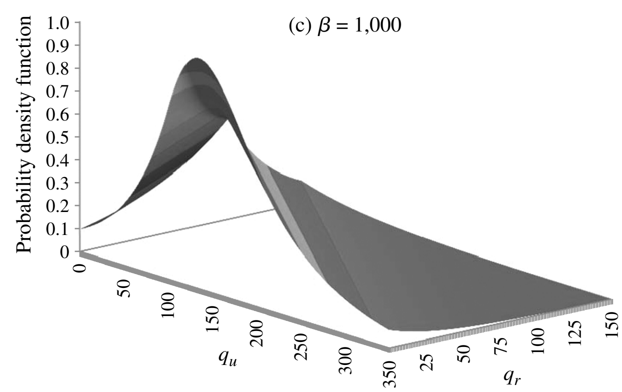


Table 8 Estimation Results for the Bounded Rationality Parameter (β)

Setting	DR_T	DR_E	β^*	$LL(\beta^*)$	$LL(\beta=1)$
LCZP	1	0.595	379	−8,666.45	−458,596.08
LCLP	1	0.410	321	−9,712.32	−365,112.21
LCHP	0	0.257	75	−6,306.07	−106,687.51
HCZP	1	0.499	235	−9,143.98	−265,248.69
HCLP	0	0.311	96	−7,729.88	−67,557.59
HCHP	0	0.249	99	−8,218.90	−189,132.41

decision that we observe in the experiment can be thought of as a result of boundedly rational decision making on the part of subjects.

Comparison of the MLEs of β^* in the six different settings also suggest systematic differences in the quality of decision making. The β^* values in the three settings in which it is optimal to source exclusively from the unreliable supplier (LCZP, LCLP, and HCZP) are 379, 321, and 235, respectively. Interestingly, in the settings in which only the reliable supplier should be used, the β^* values are 75, 96, and 99. Furthermore, we also estimated β^* under three other conditions: (i) when the β^* is assumed to be the same for LCZP, LCLP, and HCZP conditions, β^* turns out to be 306; (ii) the joint β^* for LCHP, HCLP, and HCHP settings is 90; (iii) and the joint β^* for all six settings is 205. The likelihood ratio tests using the χ^2 statistic above confirm that the bounded rationality parameters are significantly different among the above three models.

This indicates that subjects make better decisions when the optimal strategy is to order exclusively from the reliable supplier, supporting our result in §4.2. Note that risk aversion would push subjects in all settings to allocate a greater share of orders to the reliable supplier. Therefore, risk aversion would exacerbate the effect of bounded rationality when it is optimal to stay away from the reliable supplier; on the contrary, when the reliable supplier is the optimal choice, risk aversion would naturally counteract the effect of bounded rationality by channeling more orders to the reliable supplier. So, although risk aversion is not able to fully explain the diversification phenomenon, it is perhaps able to explain relatively better decision making by subjects when the optimal choice is to use only the reliable supplier.

6. Robustness Checks

The primary insight of this paper based on our experiments—that subjects display a tendency to diversify significantly more than what is theoretically optimal—turns out to be quite robust. In this section, we discuss some of the conditions under which the insight continues to hold.

Economic Incentives for Subjects. Previous research has shown that performance-based monetary incentives can play an important role in the results of behavioral experiments. For example, the outcomes of the probability matching experiments differ considerably based on whether or not the payments to the subjects are tied to their performances (Shanks et al. 2002). As discussed in §4, in our case, on average, more than 60% of the payments to the subjects were based on their profit performances (compared to the theoretical optimal), implying that they had a significant economic incentive for optimal decision making. However, results from a quite similar laboratory experiment where the "compensation" for every subject was only the same amount of course credit for participation (i.e., the incentive was nonmonetary and not tied to performance) were consistent with those from §4.2 (see Appendix B for details). Specifically, as is evident from Table B.1, the diversification ratios (i.e., DR_E) for the six settings in that case are also significantly different from the theoretical optimals (i.e., DR_T) like in Table 3 of this paper. This suggests that the diversification tendency persists irrespective of whether the subjects are paid or unpaid. Even when we look at the estimated bounded rationality parameter β^* for unpaid subjects in Table B.1, they are significantly different from zero (like for paid subjects in the previous section). However, in general, β^* is lower for paid subjects, signifying that monetary incentives improve decision making in our context.

Academic Background of Subjects. It might be hypothesized that since our subjects are business students, they may have been exposed to finance courses, which focus on the merits of diversification, resulting in the tendency we observe in our experiments. To investigate this issue, we included a specific question in our questionnaire to ascertain whether or not subjects are familiar with the diversification strategy from previous finance courses. It turns out that between 40% and 53% of the subjects were familiar across the six settings (with an overall average of approximately 45%), whereas the rest were not. However, both of these groups showed a significant amount of order diversification in our experiments, and, in general, there was not a significant difference between the diversification ratios of the two groups. More details are provided in the online supplement.

Experience of Subjects. To account for the time to develop experience about the game, we also analyzed our setting by ignoring the first 15 (respectively, 20) periods. As is evident from Table 9, a focused analysis on the orders from the last 15 (respectively, 10) rounds of the experiment continues to support our main findings related to diversification tendency discussed in §4.2. In this context, it is important to point out that, although the diversification effect remains strong, our subjects improve their decisions over time, which is in line with findings in the existing literature (Siegel 1964, Prasnikar and Roth 1992, Roth and Erev 1995,

Table 9 **Average of Diversification Ratios in Different Periods**

		First 15 vs. last 15 periods			First 20 vs. last 10 periods		
Setting	DR_T	Periods 1–15	Periods 16–30	*p*-value	Periods 1–20	Periods 21–30	*p*-value
LCZP	1	0.575	0.656	0.000	0.587	0.672	0.000
LCLP	1	0.399	0.447	0.009	0.410	0.448	0.018
LCHP	0	0.317	0.265	0.002	0.308	0.257	0.004
HCZP	1	0.466	0.559	0.000	0.487	0.564	0.000
HCLP	0	0.326	0.318	0.347	0.324	0.319	0.419
HCHP	0	0.263	0.249	0.202	0.255	0.259	0.431

Note. Values provided are averages of DR_{Et} in different epochs.

Bolton and Katok 2008). We demonstrate this by testing the following hypothesis.

Hypothesis 3. *With experience, subjects achieve diversification ratios (and optimal order quantities) that are closer to the theoretical optimum.*

To measure any learning accrued over time, we calculate the average diversification ratio for each round and test whether it approaches the theoretical optimum over time. Following §4.2, the experimental diversification ratio may be defined for round t as

$$DR_{Et} = \frac{\sum_{i=1}^{n} q_{uit}}{\sum_{i=1}^{n}(q_{uit} + q_{rit})}.$$

If subjects display improvements due to learning in any setting, we should observe an appropriate increase or decrease in DR_{Et} with t, depending on whether the theoretical DR_T for the setting is 0 or 1. In all settings, we note some improvement in performance over time. To test whether these effects are statistically significant, we divide the 30 period horizon into two 15-period epochs. If subjects learn over time, we should find that the average performance in Periods 16–30 is closer to the theoretical DR_T than the average performance in Periods 1–15. These results are reported in Table 9. In each setting, the average performance of subjects in the second 15 periods shows an improvement over the first 15 periods. The improvements are statistically significant in four settings, namely, LCZP, LCLP, LCHP, and HCHP. Note that analysis based on normalized profit performance of experimental subjects in each period also yielded similar conclusions about the learning hypothesis. We caution that our results are based on fewer number of periods than prior works that have specifically focused on the impact of learning (Bolton and Katok 2008, Lurie and Swaminathan 2009). To ensure that our findings are robust, we also conduct the same comparison by separating the 30 period horizon into the first 20 and the last 10 periods. Based on Table 9, our previous conclusions continue to hold.

Measurement Techniques. We use the expression in (1) to define average diversification ratio in this paper. However, we can envision the following two alternative definitions for this ratio:

$$DR_{E1} = \frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{30}\left(\frac{q_{uit}}{q_{uit} + q_{rit}}\right),$$

$$DR_{E2} = \frac{(1/n)\sum_{i=1}^{n}\sum_{t=1}^{30} q_{uit}}{(1/n)\sum_{i=1}^{n}\sum_{t=1}^{30}(q_{uit} + q_{rit})}.$$

Once again, it turns out that the main insights of §4.2 remain valid even with the above alternative definitions. In a similar fashion, we note that the main results of §4.2 in terms of the significant diversification in order allocation and consequent impact on profits continue to hold even if we use the *median* measure under the six settings, rather than mean, for statistical testing (refer to the online supplement for details).

7. Concluding Discussion

In search of efficiency, supply chains in many industries are becoming increasingly complex and global in nature and are facing increasing risk of possible disruptions in their procurement systems. In this context, managing the risk of production by carefully selecting suppliers has become a critical challenge. Naturally, this issue has attracted some much deserved attention in the academic literature in the past decade; several useful theoretical models (based on perfectly rational players) for balancing and minimizing supply risk have resulted from this effort (Tang 2006, Sodhi et al. 2012). A relevant issue in this context is the fact that sourcing decisions in many organizations are still influenced at least partially by the behavioral tendencies/biases of individual managers. Although this has been established through surveys in the extant literature (refer to §§1 and 2 for references), experimental study of procurement strategy with an asymmetric supplier base remains a relatively open question. In this paper, we attempt to fill this gap regarding how individuals make sourcing decisions among multiple (asymmetric) suppliers in the face of possible supply disruption.

In our setting, the firm must decide how many units for a particular product to order from a reliable, but expensive, supplier and from an unreliable, but less expensive, supplier. To focus on supply risk, we create a stylized setting in which demand for the product is deterministic, and show that sole sourcing from one of the suppliers is optimal. (Which supplier is optimal depends on the cost and risk parameters.) Six different experimental variations of this model were presented to paid subjects, with two levels of cost differences and three levels of supply risk differences between the two suppliers. The parameters were chosen so that sole sourcing from the reliable supplier and from the unreliable supplier were each optimal in three of the settings. Although subjects demonstrated an understanding of the basic tradeoff between cost and risk in managing suppliers, their decisions deviated from theoretical predictions in a systematic manner. Our experimental observations uncover an interesting phenomenon, and the following analysis provides a possible explanation for it.

Diversification Strategy. There is strong evidence that subjects in our experiment adopt a diversification strategy by ordering from both suppliers instead of ordering exclusively from one supplier (which is the optimal strategy in our settings). This observation is present even in settings where it is optimal to not order from the risky supplier, implying that risk aversion by itself does not explain the results, even though it may be present in conjunction with bounded rationality. In fact, subjects are "close" to the optimal solution of sole sourcing in less than one-third of the ordering instances. Whereas supply diversification in practice has been theoretically explained as an optimal strategy to hedge risks (Babich et al. 2007) or motivate competition between suppliers (Tomlin and Wang 2005), our experiments suggest there is a possibility that diversification may arise in practice even due to bounded rationality of the decision makers (see below). This implies that firms must actively review sourcing arrangements for influences of unnecessary diversification.

Effects of Cost/Risk Factors and Learning. Subjects do consider both cost differences and disruption probability in determining what fraction of the demand must be allocated to each supplier. As our comparison between different settings reveals, the fraction of orders that go to the unreliable supplier decreases if that supplier's cost or risk increases. This suggests that when subjects are made aware of the cost–risk trade-off, and encouraged to consider the differences, they can perhaps make better quality decisions. Furthermore, subjects, in general, seem to show an ability to improve their decisions over time as their exposure to the problem increases. Therefore, although simple heuristics may drive ordering decisions in the beginning, continued exposure to the problem appears to (partially) improve decision making.

Subjects are Boundedly Rational. We provide a rationale as to why the subjects in our experiments behave the way they do. Specifically, we ascribe it to boundedly rational decision making on their part, because of which, although they are more likely to choose better options, they will most probably not choose the best one. This particular behavior is strongly present in all our experimental settings. Subjects seem to be especially boundedly rational when they should opt for the cheaper supplier. It might not be possible for real-life managers to be perfectly rational as assumed in many models; however, making them aware about underlying tendencies, which might affect their decisions, could potentially result in supply chain cost savings. Note that even though risk aversion of subjects by itself does not explain our experimental observations, this behavior might still be present in our setting (in addition to bounded rationality).

Robustness and Profit Implications. There are two other reasons as to why the above phenomenon might be of interest in practice. First, based on our experimental settings, the above diversification strategy can result in significant profit penalty. As alluded to above, these losses seem to be especially significant when the optimal strategy is to use only the cheaper (and more risky) supplier. Moreover, the diversification tendency result seems to be quite robust. It exists even when we use unpaid subjects, when we account for the academic background of the subjects, or when we test with alternate measurement approaches. This provides credence to the argument that our experimental results might indeed be valid in practice.

To focus on the dimension of supply risk, we created a stylized setting in which supply uncertainty was the salient issue. A natural limitation of this approach is that practical realities such as demand uncertainty had to be ignored. Future work should consider more realistic procurement problems by including aspects like demand stochasticity, multiple unreliable suppliers, and information asymmetry. Although our experiment provides limited support to the learning hypothesis, a future study over many more decision periods would be able to definitively identify the importance of experience. Last, though our paper offers behavioral insights into supply risk management, we do not consider the competitive and dynamic reasons for having a diverse set of suppliers or experiment with real-life procurement professionals. These represent other directions for potential future experimental studies.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2013.0453.

Acknowledgments

The authors thank editor Stephen C. Graves, the associate editor, three anonymous reviewers, Elena Katok, Ashesh Mukherjee, and Diana Wu for their constructive comments and feedback on this paper. Haresh Gurnani's research was partially supported by grants from the Leslie O. Barnes Foundation, the Provost's Research Award, and the U.S. Department of Education Title VI (CIBER) grant. Saibal Ray was supported in part by research grants from the Natural Sciences and Engineering Research Council of Canada [Grant NSERC RGPIN 249493-12] and the Social Sciences and Humanities Research Council of Canada [Grant SSHRC 214832].

Appendix A. Experimental Setup

Figure A.1 Screenshot of Order Placement Interface Used in the Experimental Setup

In order to get paid, you need to input your name and email address and answer ALL questions.

Please input your name

Please input your email address

Description of problem

You are selling a product whose retail price is $45 per unit. The demand for the product is a constant amount equal to 100 units. You can order the product from two suppliers: One expensive but reliable supplier (R) and a second cheaper but unreliable supplier (U).
Supplier R will deliver exactly what is ordered from him. However, for the unreliable supplier (U), there is a 20% chance of full disruption. When this happens, supplier U will deliver zero units. Even if there is no disruption, supplier U will deliver only a fraction alpha of the ordered quantity (where alpha can be any number between 0.5 and 1 with equal chance). For example, if you order 50 units and alpha = 0.6, then supplier U will deliver (50*0.6) = 30 units.
The purchasing cost from the reliable supplier R is $30 for each unit and the purchasing cost from the unreliable supplier U is $18 per delivered unit.
Note that, at the end of the month, if you cannot satisfy all demand, you will not receive the payment of $45 for each unit of unsatisfied demand.
On the other hand, if you have leftover products, they will have no value. What are your order quantities from the reliable and unreliable suppliers in order to maximize your profits?

For month 1, please enter your TWO decision below:

Your order quantity from the unreliable supplier (U) is

Your order quantity from the reliable supplier (R) is

Appendix B. Economic Incentives

Students were also recruited to participate in an experiment nearly identical to the one described in §4.1. The two changes to the setting were that (i) the cost of the unreliable supplier in the LC settings was $c_u = \$15$ (whereas in the experiments of the paper the corresponding cost was $18), and (ii) any remaining units at the end of each period incurred a disposal cost of $5. The theoretical optimal strategy is identical to our main experiment; that is, it is optimal to sole source in this case as well, with the unreliable supplier being optimal in the LCZP, LCLP, and HCZP settings (and the reliable supplier being optimal in the remaining three settings).

More importantly, students in this experiment were not paid based on their performance. They only received course credit for their participation. As reported in Table B.1, we find that the fundamental results regarding diversification continue to exist even in this unpaid setting. In general, paying subjects did not seem to affect the experimental outcomes significantly, although payments seem to improve decision making, as evident from β^* values.

Table B.1 Experimental Diversification Ratios for Paid and Unpaid Subjects

		DR_E		β^*	
Setting	DR_T	Paid	Unpaid	Paid	Unpaid
LCZP	1	0.595	0.575	379	494
LCLP	1	0.410	0.474	321	390
LCHP	0	0.257	0.308	75	96
HCZP	1	0.499	0.455	235	364
HCLP	0	0.311	0.295	95	216
HCHP	0	0.249	0.214	99	83

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