Supply Risk Mitigation via Supplier Diversification and Improvement: An Experimental Evaluation

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Due to the trend towards decentralization and greater complexity in supply chains, companies are increasingly exposed to supply risks. Various strategies to mitigate supply risks have been developed using modeling-based approaches, including risk diversification by dual sourcing and direct investment to improve supplier performance. Yet, despite the overwhelming evidence that managerial decisions are influenced by behavioral factors particularly under risk and uncertainty, such behavioral factors are typically not considered by previous theoretical studies. In this paper, we use controlled lab experiments to evaluate the performances of dual sourcing and single sourcing with supplier improvement strategies to mitigate risks of a buyer facing suppliers with different costs and risk profiles, and develop behavioral theories to elucidate the decision-making process under supply risks more effectively. With dual sourcing, human buyers do not diversify their orders effectively (relying on a more even allocation of orders between suppliers than theory suggests) and exhibit quantity hedging behavior. To explain this phenomenon, we propose and empirically validate a behavioral theory in which human buyers choose order quantities to minimize their disutility from order allocation errors between suppliers. Human buyers use the single sourcing with supplier improvement strategy relatively effectively, despite being subject to supplier selection errors due to bounded rationality.

Key words: supply risks, diversification, supplier improvement, behavioral operations

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1. Introduction

As the companies outsource their manufacturing or services to other companies to focus on their core competencies, they are becoming increasingly dependent on their suppliers to perform well. Despite achieving lower costs, outsourcing also leads to loss of control over the supply chain and exposes the companies to disruptions from a variety of sources, including supplier failures, worker health and safety problems, and weather events (Sheffi 2005).

Increasing exposure to supply chain risks has been widely documented in industry reports as well: according to the Chief Supply Chain Officer Report (2012), more than two-thirds of supply chain executives are concerned about shipping disruptions, incidents at supplier facilities, and the failure of key suppliers (Lee et al. 2012). Similarly, 69% of respondents to the McKinsey Global Survey in 2010 reported that their supply chain risk increased over the past five years and that
they were expecting this trend to continue (Gyorey et al. 2010). Supply chain disruptions can have substantial negative economic consequences, resulting in significantly lower operating and stock market performance for a firm (Hendricks and Singhal 2005a, b).

What is the best way to mitigate supply risks? Many modeling-based studies have tried to answer this question in the operations management (OM) literature and different sourcing mechanisms have been proposed. One of the most popular approaches is multiple sourcing, in which a buyer firm diversifies risk through sourcing from multiple suppliers (Anupindi and Akella 1993, Babich et al. 2007, Dada et al. 2007, Federgruen and Yang 2009, Wang et al. 2010, Yang et al. 2012). This is an indirect risk mitigation strategy as the buyer considers the suppliers’ risk profiles as exogenous and decides how much to buy from each. Alternatively, a buyer firm may commit to sourcing from a single supplier, but may take on a direct role to improve its supplier’s performance (Wang et al. 2010, Wang et al. 2014); that is, the buyer firm may invest in a supplier to reduce the probability and magnitude of its disruptions. Single sourcing with supplier improvement (SSI) is a direct risk mitigation strategy since the buyer firm treats the supplier’s risk profile as endogenous. Both of these strategies are demonstrated to be effective in theory (Wang et al. 2010).

Yet, whether managers can use these strategies effectively in practice remains an open question. In Zsidisin et al. (2000), managers stated that despite using multiple sources for strategic parts, they may not be effectively mitigating supply-related risks. Jain et al. (2016) show in a large-scale empirical study that supplier diversification is associated with slower recovery from supply interruptions and posit that there is ambiguity on the efficacy and value of supplier diversification in practice. Similarly, an empirical and case-based body of literature on supplier improvement points to a variety of outcomes. Krause et al. (2007) find that direct supplier involvement may be particularly influential at improving the reliability performance of the suppliers (as reported in surveys by the managers of buyer firms and their suppliers). Despite finding support for the benefits of supplier improvement through survey data and case studies, Handfield et al. (2000) point out that not all companies succeed in their supplier improvement efforts. In particular, buyers may be reluctant to fully pursue supplier improvement as a result of failing to evaluate potential benefits in the future. Finally, through a series of field studies conducted with multinational firms and their suppliers in the developing countries, Locke (2013) finds mixed evidence about the success of supplier improvement activities.

A common feature of the modeling-based papers in OM on supply risks (and one potentially hurting their practical relevance) is that decision makers are assumed to be expected profit maximizers. However, Zsidisin et al. (2000) provides practical evidence that supplier risk assessment is conducted at a strategic level by managers, who then use this assessment in supplier selection, development and business allocation decisions. Moreover, in assessing risks, managers often rely
on qualitative measures and their own judgement. Despite the evidence that managerial decision making under risk and uncertainty is affected by behavioral factors (March and Shapira 1987, Qualls and Puto 1989), these factors have received limited attention in the context of supply risks in the OM literature.

Given the gap between theory and practice on sourcing strategies to mitigate supply risks, our goal is to evaluate these strategies in a controlled lab environment when human decision makers operationalize each strategy. We aim to answer the following research questions in this paper: (1) How effectively do human decision makers use different sourcing strategies (such as dual sourcing or SSI) to mitigate supply risks? (2) What behavioral factors may prevent decision makers from using these strategies effectively? and (3) When/how do these behavioral factors change the conclusions of standard theory? Our goal is to identify the behavioral influences on decision making in this context and incorporate them into theory. This way, we can evaluate supply risk mitigation strategies more accurately and prescribe more effective strategies to managers.

For this purpose, we first conduct controlled lab experiments. We study a two-tier supply chain with a buyer (human) facing two (computerized) suppliers with different cost and risk profiles. One of the suppliers has a lower unit cost than the other, but is also subject to random capacity disruptions. The buyer procures from the suppliers and sells to customers to satisfy constant demand. We operationalize two different sourcing strategies (dual sourcing vs. SSI) as different treatments in our experiments. We also consider the effect of sourcing commitments by studying alternative decision sequences under SSI: the buyer may choose the effort to improve a supplier either before or after supplier selection, which correspond to late and early commitment scenarios, respectively. Through lab experiments, we identify systematic deviations from theory in observed behavior. We then develop behavioral models to explain these deviations. Finally, we reconcile theory and observed behavior by extending the theoretical models of dual sourcing and SSI to include behavioral influences.

We observe systematic deviations from theory in how effectively human subjects use dual sourcing and SSI. In response to the cost vs. supply risk trade-off, human buyers do not diversify their orders as effectively as in standard theory with dual sourcing and allocate orders more evenly between suppliers than theory. In addition, human buyers use quantity hedging (presumably to mitigate risk) and order more than customer demand. We show that these observations cannot be explained by commonplace behavioral effects such as naïve diversification, risk aversion, or stockout/leftover aversion. We propose a behavioral theory of order allocation error minimization to capture the observed behavior: according to this theory, a buyer experiences disutility from not having allocated her total procurement optimally between suppliers after observing the impact of a disruption on a supplier’s available production capacity. We empirically validate that a model of order allocation
error minimization and random errors fits the data remarkably well. Under SSI, human buyers are effective at making order quantity and improvement effort decisions at the individual supplier level, but they can deviate from standard theory in supplier selection decisions. We find support for a random errors model to capture improvement effort and supplier selection behavior in our experiments.

We demonstrate the relative efficacy of direct risk mitigation through supplier improvement over indirect risk mitigation through dual sourcing, consistent with standard theory predictions for our experimental setting. The buyers are relatively successful in evaluating the trade-off between the supply risk and the improvement cost in choosing their effort to improve a supplier. However, in all treatments, behavioral inefficiencies originate primarily from the buyer’s sourcing allocation decisions between suppliers (i.e., supplier selection for sole sourcing in SSI and order quantity decisions with dual sourcing). These inefficiencies are particularly pronounced with dual sourcing: anticipating disutility from ex-post order allocation errors may prevent managers from diversifying orders effectively, and hence, from devising a proactive risk-management strategy. Therefore, eliminating such behavioral inefficiencies (potentially with decision support tools) present significant opportunities for increasing the buyer’s profit.

In Section 2, we review the relevant literature and describe our contributions. In Section 3, we introduce the theoretical model that our experiments are based on and develop hypotheses based on the predictions of standard theory. In Section 4, we describe our experimental design. We summarize our experimental results in Section 5 and develop the behavioral models to capture our observations in Section 6. We conclude the paper with discussions and managerial insights in Section 7.

2. Literature Review
2.1 Theoretical and Empirical Literature on Supply Risk Management

We contribute to the nascent field of supply chain risk management, for which Sodhi et al. (2012) identified a methodology gap and called for more empirical studies to bridge the gap between theory and practice. Within this field, there is an extensive body of theoretical literature (Tang (2006) provides an excellent review; we also refer readers to Gurnani et al. (2014) and Wang et al. (2010) and the references therein). The theoretical setting of our paper builds on Wang et al. (2010) (with notable modifications reviewed in Section 3 to facilitate the implementation in the lab environment). Within this context, we focus our attention to sourcing and supplier improvement strategies. The prevalent assumption in this theoretical literature is that the decision makers are fully rational. Our work serves as an experimental evaluation of the theoretical predictions of the prior literature. We aim to reconcile theory and observed behavior by developing behavioral models and incorporating them back into the theoretical models of supply chain risk mitigation to increase their descriptive and prescriptive power.
2.2 Behavioral Operations Management

Our work contributes to the emerging stream of literature within behavioral OM on decision making under supply uncertainty. Below, we review the related literature within behavioral OM and underline our differences and contributions.

Experimental work on demand risks: The behavioral operations management literature has extensively analyzed how managers match supply and demand under demand uncertainty (i.e., the classical newsvendor problem) (Schweitzer and Cachon 2000, Su 2008, Ho et al. 2010, Ren and Croson 2013, Ockenfels and Selten 2014, Tong and Feiler 2016). Even though managerial decision making under demand-side risks is well studied from a behavioral perspective, how managers match supply and demand under supply uncertainty remains relatively less explored. Moreover, our results show that behavioral factors influential under demand-side risks (such as the disutility from stockouts/leftovers) cannot explain decision making under supply-side risks, validating our behavioral focus on supply risk management.

Empirical literature on the perception of supply risks: There is an empirical and case-based body of literature that examines supply risk definitions and perceptions of purchasing managers and that identifies the behavioral and organizational factors influencing these perceptions (Zsidisin et al. 2000, 2004, Zsidisin 2003, Ellis et al. 2010). While the primary focus of this literature is on the assessment of supply risk, how perceptions of that risk translates into managerial decisions on supplier selection, improvement and/or order allocation has not yet received sufficient attention in this literature. Therefore, our paper complements this literature by studying decision making on supplier selection, improvement and order allocation in an incentive-aligned environment.

Experimental literature on dual sourcing: The closest papers to our work in this domain are Gurnani et al. (2014), Goldschmidt et al. (2014), and Csermely and Minner (2015). We review the similarities and differences between their work and ours below.

In Gurnani et al. (2014), the authors consider a buyer procuring products from two heterogeneous suppliers who are different in their costs and reliabilities. In their setting, it is theoretically optimal to sole source either from the more costly and reliable supplier or from the more risky and cheaper supplier. Yet, the authors observe that human subjects diversify orders between the two sources. The authors establish that bounded rationality of subjects may provide a rationale for this phenomenon.

Our paper is different from Gurnani et al. (2014) in three important ways: first, we consider a setting where dual sourcing is theoretically valuable and we examine how effectively human participants use this mechanism to manage supply risks. Camerer (2003, p. 216) notes that in experiments with boundary equilibrium predictions, it is almost impossible to differentiate any systematic deviation from theory from playing the equilibrium strategy plus being subject to
random errors. Therefore, our setting (which allows for interior equilibrium predictions) can be better suited to test alternative behavioral theories compared to the setting of Gurnani et al. (2014) (for which sole sourcing is the unique equilibrium). Consequently, we observe two different results. While documenting the diversification tendencies similarly to Gurnani et al. (2014), we also show that human subjects exhibit quantity hedging behavior to tackle supply uncertainty, inflating the total order quantity above customer demand. In addition, we observe that bounded rationality by itself cannot capture all of the dynamics in our data. We propose and empirically validate a new behavioral model: according to this model, subjects choose order quantities to minimize their disutility from order allocation errors between the two suppliers. This model directionally captures both order diversification and quantity hedging behavior in our data well.

Goldschmidt et al. (2014) analyze the trade-off between transaction costs and supply disruption costs in supplier base selection. In their model, engaging with more suppliers leads to higher transaction costs while creating risk pooling and reducing supply disruption costs. Given this trade-off, they analyze supplier base selection decisions. In their setting, suppliers are identical in their risk and cost profiles. However, in many theoretical and practical settings, suppliers are highly heterogeneous, adding an important layer of complexity in supplier selection decisions. Therefore, we study a setting where suppliers are heterogeneous in terms of their costs and risks, and we evaluate the effectiveness of two different supplier risk management practices in this setting through behavioral experiments.

In Csermely and Minner (2015), the authors examine human participants’ dual sourcing decisions (i.e., order allocation decisions between a fast and expensive versus a slow and cheap supplier) to match supply and demand under demand uncertainty. They find that human subjects overutilize the fast and expensive option. Their observations are consistent with reference-dependent preferences due to the disutility from stockouts/leftovers proposed by Ho et al. (2010). Our work differs from theirs in two important ways: first, they consider the cost versus speed trade-off in the presence of demand uncertainty whereas we consider cost versus supply risk trade-off in the presence of supply uncertainty. Second, we establish that our results cannot be explained by stockout/leftover aversion. Instead, we propose a theory of order allocation error minimization which, together with bounded rationality, captures our observations effectively.

**Experimental work on supplier improvement:** To the best of our knowledge, ours is the first paper to study supplier improvement and selection decisions jointly in an experimental setting in the OM literature. Hu et al. (2017) study the supplier development programs in a capacity investment context. In their setting, the suppliers develop capacity where the buyer partially compensates for the capacity investment. However, their work focuses on the suppliers’ capacity investment
decisions in a competitive environment whereas our experiments focus on a buyer firm’s supplier improvement and selection decisions in the presence of supply uncertainty.

**Behavioral models of reference dependence:** To explain the behavior of our human subjects in dual sourcing experiments, we develop a behavioral theory of order allocation error minimization. According to this theory, the buyer experiences disutility ex-post from not having allocated the order quantities optimally between suppliers after observing the magnitude of a supply disruption. As such, our formulation is connected to the models of reference-dependent preferences (Thaler 1985, Koszegi and Rabin 2006, Ho et al. 2010). To the best of our knowledge, ours is the first study within the experimental literature in OM to capture reference dependence in separate dimensions in a multi-dimensional decision making environment.

3. Model

We consider the problem of a buyer firm sourcing from two potential suppliers, S1 and S2, which are heterogeneous in their cost and risk profiles. The buyer firm orders products from the suppliers and sells them to the customers at a unit price of $r$. The customer demand for the buyer firm’s product is deterministic and equals $D$. The buyer pays pre-determined and fixed unit wholesale prices $w_1$ and $w_2$ for each product delivered by S1 and S2, respectively.

A supplier may deliver less than the buyer’s order due to its limited production capacity. Each supplier has design capacity $K$, which is the maximum production that each supplier can achieve. Furthermore, the supplier’s effective capacity may be less than the design capacity due to random disruptions. S1 is subject to random capacity disruptions while S2 is fully reliable (i.e., S2’s design and effective capacity are equal). As in Wang et al. (2010), S1’s effective capacity is $K - \xi$ where $\xi$ is a random variable that follows a continuous distribution $G(\cdot)$ with support $[0, K]$. S1 is also the cheaper supplier; $r > w_2 > w_1 > 0$. Throughout the text, we refer to S1 and S2 as the “risky” and “reliable” suppliers, respectively.

Our model follows Wang et al. (2010), albeit with certain modifications. Wang et al. (2010) consider a scenario where both suppliers are subject to capacity disruptions. We focus our attention to a setting with one reliable and one risky supplier because of our interest in supply risk management in the presence of supplier heterogeneity and to facilitate the implementation in behavioral experiments. Moreover, we assume that the customer demand $D$ is deterministic and that each supplier’s design capacity is sufficient to cover the buyer firm’s customer demand, $K > D$, (i.e., no capacity limitation in the absence of disruptions) to reduce the complexity of the decision task.

We consider two alternative strategies for the buyer firm to manage risk in its supplier base, dual sourcing and SSI. With dual sourcing, the buyer firm chooses the order quantities from both suppliers. With SSI, the buyer sources exclusively from one of the suppliers and has the option to
exert costly improvement effort to reduce the impact of the random capacity disruptions at the risky supplier\(^1\). We detail each strategy and compare them below.

### 3.1 Dual Sourcing

With dual sourcing, the sequence of events is that the buyer firm first chooses the quantities to order from each supplier. Then, S1’s random capacity reduction is determined and its effective capacity is realized. Finally, both suppliers deliver the minimum of the buyer’s order quantity and their effective capacity. Let \( q_1 \) and \( q_2 \) represent the order quantities from S1 and S2, respectively. The buyer’s optimization problem is

\[
\max_{0 \leq q_1, q_2 \leq K} \Pi(y_1(q_1), q_2) \quad \text{with} \quad \Pi(y_1(q_1), q_2) := E[r \min\{D, y_1(q_1) + q_2\} - w_1 y_1(q_1) - w_2 q_2] \tag{1}
\]

wherein the expectation is with respect to \( \xi \) and \( y_1(q_1) \) is the quantity delivered by S1;

\[
y_1(q_1) = \min\{q_1, (K - \xi)\}. \tag{2}
\]

Without loss of generality, we impose that \( q_1 \) and \( q_2 \) are less than the design capacity \( K \) because procurement quantities above the supplier’s capacity are weakly dominated. The following proposition summarizes the buyer firm’s optimal procurement quantities with a dual sourcing strategy.

**Proposition 1.** The buyer’s optimal order quantities from S1 and S2 are given by

\[
q_1^* = \min \left\{ K - G^{-1}\left(\frac{r - w_2}{r - w_1}\right), D \right\}, q_2^* = D - q_1^*.
\]

In Proposition 1, the optimal allocation of the buyer’s order quantities is driven by the cost benefit S1 provides relative to S2 (as measured by \((r - w_2)/(r - w_1)\)) and the magnitude of the capacity disruptions faced by S1. An increase in S1’s cost benefit and/or a reduction in the magnitude of capacity disruptions (in first-order stochastic dominance) increases the buyer firm’s procurement quantity from S1. In certain settings, the buyer may prefer to source from only the most attractive supplier because of significant price or disruption risk differences between the suppliers.

The total procurement quantity is always equal to the customer demand and hence the buyer never overorders in this setting. Wang et al. (2010) observe that quantity hedging through overordering can be valuable when the buyer firm sources from multiple suppliers because it protects the firm against capacity limitations in the event that one supplier experiences a capacity shortage. In our setting, however, where only one supplier is subject to random capacity disruptions, quantity hedging is theoretically not preferred.

\(^1\) In practice, the improvement effort can correspond to a buyer sending its employees to supplier facilities for real-time problem resolution and sharing expertise to eliminate production problems and delays, as Boeing did to eliminate problems in its supply chain during the development of the 787 Dreamliner (McDonald and Kotha 2015).
3.2 Single Sourcing with Supplier Improvement

With SSI, the buyer firm exclusively sources from one supplier and has the option to exert costly effort to improve S1 to reduce the supplier’s capacity disruption risk\(^2\). The buyer firm’s effort, if successful, will improve the reliability of S1. That is, if the buyer exerts improvement effort \(z\) and this effort is successful, the supplier’s new reliability level will be \(a(z)\), where \(a(\cdot)\) is a twice differentiable and strictly increasing function of \(z\). The random capacity disruption after a successful improvement effort is represented by the nonnegative random variable \(\xi\), with the continuous distribution function \(G_s(\cdot, a(z))\). A positive improvement effort, if successful, decreases (in first order stochastic dominance) the random capacity disruption faced by S1; \(G(x) = G_s(x, a(0)) \leq G_s(x, a(z))\) for \(x \in [0, K]\) and \(z > 0\). Furthermore, \(G_s(\cdot, a(z))\) is differentiable, nondecreasing and concave with respect to \(a\). The improvement effort exhibits diminishing returns; \(a(z)\) is concave with respect to \(z\). The buyer firm incurs a cost of \(m\) per each unit of effort exerted to improve the first supplier. As pointed out in Wang et al. (2010) and the supplier improvement literature referenced therein, improvement initiatives are not always successful. To reflect that in our model, we assume that the buyer firm’s improvement effort may succeed with an exogenously determined probability \(0 < \theta < 1\). If improvement efforts are not successful, capacity reduction faced by S1 is represented by the random variable \(\xi\), as in the dual sourcing scenario.

The literature on supplier improvement (e.g., Handfield et al. 2000, Krause et al. 2007, and Locke 2013) identifies buyer commitment as an important determinant of the success of supplier improvement activities. Thus motivated, we study variations of SSI together to reflect different degrees of buyer commitment. Since improvement efforts may not always succeed, the buyer firm may delay choosing the sole supplier until after observing the outcome of the improvement effort. Hence, we consider two variations of SSI: early versus late commitment. With early commitment, the buyer firm chooses and commits to a supplier first before observing the outcome of its effort to improve S1. With late commitment, the buyer firm can incur a cost to improve S1 and observes its success/failure before selecting the supplier to exclusively source from. These variations will later be used for two purposes: first, for our comparisons of dual sourcing and SSI, they will be helpful in measuring the robustness of our results to alternative decision sequences and commitment strategies. Second, the comparison between early and late commitment will help us to identify whether human subjects use one commitment strategy more effectively than the other.

**Early commitment:** With early commitment, the buyer firm first chooses the supplier to source from. If the buyer chooses S1, the buyer can exert an effort to reduce S1’s disruption risk. After

\(^2\)While the buyer firm may utilize multiple sourcing and supplier improvement in tandem, we focus our attention to them in isolation as pure strategies to better test and compare their effectiveness in experiments.
observing the outcome of the improvement effort, the buyer determines how much to order. Alternatively, if S2 is chosen, the buyer need not exert effort and determines only the order quantity.

If the buyer chooses to source from S1, the buyer’s expected profit maximization problem is

$$\Psi_1 = \max_{z \geq 0} \left\{ \theta \max_{0 \leq q_1 \leq K} \psi_{1,s}(z, q_1) + (1 - \theta) \max_{0 \leq q_1 \leq K} \psi_{1,n}(q_1) - mz \right\},$$

where $\psi_{1,s}(z, q_1)$ and $\psi_{1,n}(q_1)$ are the buyer’s expected profit after improvement success and failure given by the following expressions, respectively:

$$\psi_{1,s}(z, q_1) = E_\xi [r \min\{\min\{q_1, K - \xi_s\}, D\} - w_1 \min\{q_1, K - \xi\}|a(z)],$$

$$\psi_{1,n}(q_1) = E_\xi [r \min\{\min\{q_1, K - \xi\}, D\} - w_1 \min\{q_1, K - \xi\}].$$

If the buyer chooses to source from S2, the buyer’s expected profit maximization problem is

$$\max_{0 \leq q_2 \leq K} \psi_2(q_2) = \max_{0 \leq q_2 \leq K} \{r \min\{q_2, D\} - wq_2\}. \quad (6)$$

The buyer firm makes the supplier selection decision by comparing (3) with (6).

**Late commitment:** With late commitment, the buyer firm exerts effort to improve S1 first, and after observing the improvement outcome, chooses the exclusive supplier to source from and the procurement quantity. The buyer’s expected profit maximization can be written as

$$\max_{z \geq 0} \left\{ \theta \max_{0 \leq q_1 \leq K} \psi_{1,s}(z, q_1), \max_{0 \leq q_2 \leq K} \psi_2(q_2) \right\} + (1 - \theta) \max_{0 \leq q_1 \leq K} \psi_{1,n}(q_1), \max_{0 \leq q_2 \leq K} \psi_2(q_2) - mz \right\}. \quad (7)$$

**Early vs. late commitment:** The next two propositions characterize the buyer’s optimal procurement quantity under SSI and compare the buyer firm’s expected profit and supplier improvement effort under the two commitment strategies.

**Proposition 2.** The buyer’s optimal order quantity is $D$ regardless of commitment strategy, the buyer firm’s supplier choice, improvement effort or improvement outcome.

Consistent with Proposition 1, the buyer’s order quantity equals customer demand. This is because the demand is deterministic and overordering strictly decreases the buyer’s profit in the event that the supplier has the capacity to deliver more than the customer demand.

**Proposition 3.** (a) With early commitment, if the risky supplier S1 is chosen, the optimal improvement effort $z^*$ satisfies

$$\int_{K-D}^{K} \frac{\partial G_s(x, a(z^*))}{\partial a} \frac{da(z^*)}{dz} \, dx = \frac{m}{\theta(r - w_1)}. \quad (8)$$

(b) The buyer’s effort to improve S1 in early commitment (upon selecting that supplier) is weakly higher than with late commitment.
(c) The buyer earns weakly greater expected profits with late than early commitment.

In Proposition 3(b), the effort is weakly lower with late commitment because the effort will be valuable only when the buyer will source from S1 later. With early commitment, S1 is guaranteed to be the sole supplier if selected. Despite lower improvement effort, the buyer benefits from the sourcing flexibility late commitment provides: the buyer observes whether the improvements are successful first before selecting the sole supplier and consequently earns weakly greater profits.

3.3 Theory Predictions and Hypotheses

Suppliers are heterogenous in both cost and reliability dimensions in our model as well as in many practical applications. This setting does not allow for a full theoretical comparison of the two risk management strategies and therefore we turn to numerical methods\(^3\). We evaluate dual sourcing, and SSI with both early and late commitment for each parameter combination. Below, we report the results of dual sourcing and SSI with early commitment, however, our observations remain fully robust to commitment strategy.

**Numerical Observations:** Table 1 summarizes the performance of SSI over dual sourcing in the buyer’s expected profit with respect to cost heterogeneity and unit improvement cost for S1 and Figure 1 summarizes the buyer’s preference over the two strategies. When we consider each dimension separately, the value of SSI over dual sourcing increases with procurement cost difference between the suppliers, consistent with the prior literature. As the cost gap increases between the suppliers, the buyer allocates a higher portion of the total procurement quantity to the cheaper supplier with dual sourcing, thereby reducing the risk mitigation benefit of that strategy. With SSI, the buyer can source from the cheaper supplier and still mitigate risk by exerting a higher improvement effort. Furthermore, the value of SSI over dual sourcing decreases with the improvement cost due to the buyer’s diminished ability to mitigate risk under SSI.

Considering both dimensions together, the procurement cost gap between the suppliers has a stronger effect on the buyer’s preferences because the buyer’s sensitivity to improvement cost decreases with the cost gap (evident from the rate of change in buyer firm’s preferences when \(\Delta_{w} = 0.4\) versus when \(\Delta_{w} = 0.1\)). Therefore, when the suppliers charge significantly different wholesale prices, the buyer’s preferences remain relatively insensitive to the changes in the improvement cost.

\(^3\)We used the following set of parameters: sales price \(r = 1\), design capacity for both suppliers \(K = 120\), customer demand \(D = \{50, 60, 70, 80, 90, 100, 110, 120\}\), S1’s wholesale price \(w_1 = \{0.1, 0.2, 0.3, 0.4, 0.5\}\), wholesale price differential between the suppliers \(w_2 - w_1 = \{0.1, 0.2, 0.3, 0.4\}\), improvement success probability \(\theta = 0.8\), unit improvement cost \(m = \{0.1, 0.2, 0.3, 0.4, 0.5\}\). S1’s capacity reduction \(\xi\) follows a Uniform distribution with support \([0, K]\) and S1’s capacity reduction after improvement success \(\xi_s\) follows a Uniform distribution with support \([0, a]\) where \(a = (1/(1/K + log_{10}(1 + 0.001z)))\) (\(z\) representing the buyer’s improvement effort). We follow Wang et al. (2010) assumptions on the relationship between buyer’s improvement effort and supply disruptions. S2 does not face any disruption risk.
Table 1 Percentage increase in expected profits by SSI (early commitment) over dual sourcing

<table>
<thead>
<tr>
<th>Supplier price differential $w_2 - w_1$</th>
<th>Average</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>-1.19</td>
<td>7.34</td>
</tr>
<tr>
<td>0.2</td>
<td>2.67</td>
<td>18.95</td>
</tr>
<tr>
<td>0.3</td>
<td>9.07</td>
<td>29.78</td>
</tr>
<tr>
<td>0.4</td>
<td>14.86</td>
<td>37.83</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unit improvement cost $m$</th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>13.87</td>
<td>37.83</td>
</tr>
<tr>
<td>0.3</td>
<td>5.15</td>
<td>19.27</td>
</tr>
<tr>
<td>0.5</td>
<td>0.7</td>
<td>11.12</td>
</tr>
</tbody>
</table>

Figure 1 % of instances where SSI (early commitment) is preferred over DS (dual sourcing) with respect to the procurement cost difference between the suppliers $\Delta w = w_2 - w_1$ and the unit improvement cost $m$

cost and SSI dominates dual sourcing in most instances. Consistently, we select our parameters such that the suppliers have highly different unit prices while the unit improvement cost for the risky supplier is not too high. Within the parameter region of our numerical study, we select the following set of parameters to be implemented in the experiments: $w_1 = 0.1$, $\Delta w = 0.3$, $m = 0.2$, $D = 110$, $K = 120$, $\theta = 0.8$, and both suppliers’ margins are 0.1. Theoretical predictions under this parameter set are summarized in the first three columns of Table 2.

**Hypotheses:** First, we evaluate the effectiveness of each risk mitigation strategy as implemented by human subjects by comparing experimental decisions and profits with Table 2 (Hypothesis 1). Second, we compare each risk mitigation strategy (dual sourcing and SSI) and commitment mechanism (early versus late commitment under SSI) to measure their relative effectiveness (Hypothesis 2). According to Table 2, the buyer can increase her expected profit by 10% and 13.51% over dual sourcing using SSI with early and late commitment, respectively. The buyer’s improvement effort is the same with both commitment regimes because $S_1$ is selected as the sole supplier with early commitment and when improvements succeed with late commitment. Recall from Proposition 3(b) that the buyer’s improvement effort in theory is weakly greater with early commitment; we test this theoretical prediction at the boundary condition where the effort is the same with early and
late commitment to provide any behavioral influence responsive to the commitment level its best-shot. Considering buyer’s profits, late commitment nevertheless provides an advantage over early commitment because the buyer has the additional flexibility to select the supplier after observing the improvement outcome (Proposition 3c and Table 2). In particular, the buyer selects S2 if her efforts to improve S1 fail (because expected disruptions are more costly for the buyer than the wholesale price premium of S2) while the buyer prefers S1 if improvements succeed.

To check the robustness of our behavioral observations under dual sourcing, we have also conducted a follow-up experiment. In this experiment, the buyer faces a low margin condition with both suppliers’ wholesale prices above 0.5. In addition, due to the significant reduction in margin as a result of sourcing from S2 relative to S1, S1 becomes more attractive so that the buyer in theory should source more from S1 and less from S2. We used the following parameter set: \( w_1 = 0.64 \), \( \Delta_w = 0.21 \), \( D = 110 \), \( K = 120 \), and both suppliers’ margins are 0.1. Theoretical predictions for this experiment are summarized in the last column of Table 2.

The following hypotheses summarize our predictions.

**Hypothesis 1. (Effectiveness of Dual Sourcing and SSI).** Under each risk mitigation strategy, the buyer firm’s decisions and profits are equal to what theory predicts (Table 2).

**Hypothesis 2. (Dual Sourcing vs. SSI and the Value of Commitment).**

A. The buyer earns higher profits with SSI than with dual sourcing.

B. The buyer’s improvement effort is the same with early and late commitment.

C. The buyer can earn higher profits with late commitment than with early commitment.

4. Experimental Design

We implemented each scenario described in Table 2 as a separate treatment. We use a between-subject design where the participants played the role of the buyer firm in one of the three treatments. Our human participants were recruited from the student body of a large Southeastern public university and were compensated monetarily according to their performance. Participants
were given Web-based instructions and a quiz before the experiment. (The detailed instructions and the quiz are provided in the Online Companion.) Only the participants who answered all quiz questions correctly were recruited for the experiment. Overall, 80 participants were recruited and each made decisions for 40 rounds. The experiments lasted for approximately 1.5 hours.

The computer programs for our experiments were implemented online and the experiments were conducted at the behavioral lab of a large Southeastern public university. During the experimental session, the instructions were reviewed again and the participants had the chance to ask questions. Furthermore, the experiment included 5 rounds of training with no real money involved for the participants to become familiar with the experimental interface. To facilitate participants’ decision process, we provided them with a decision support tool (Figure EC.1 in the Online Companion).

In the dual sourcing treatments, the participants’ decision task was to choose the order quantities from each supplier. In SSI, the participants made their decisions in two stages. In SSI with early commitment, each participant selected the sole supplier and improvement effort (if the risky supplier is selected) in the first stage, and determined the quantity to order from the chosen supplier in the second stage. The participant observed whether the improvement effort was successful before ordering in the second stage. In SSI with late commitment, each participant selected the improvement effort for S1 in the first stage, without making any sourcing commitment. After that, the participant observed whether the improvement effort was successful and then determined the sole supplier and the order quantity. Table 3 provides a summary of the decisions in each treatment.

At the end of each decision round in all treatments, the computer displayed the participant’s decisions, the magnitude of the random capacity disruption and the effective capacity of the supplier(s) at that round, the delivery quantity from the supplier(s), the participants’ experimental earnings for that round and the cumulative experimental earnings. In addition, participants were able to view all the decision and outcome histories of previous rounds.

All participants were given a start-up fee of $5 at the beginning of the experiment. To provide the theory its best-shot, we designed the decision task so that any deviation from the optimal decisions led to a significant decrease in profit. For this purpose, as in Ho et al. (2010), we performed an affine transformation of their earnings in experimental dollars when we calculated their actual

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Condition</th>
<th>Decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS</td>
<td>Dual Sourcing</td>
<td>Order quantity from each supplier</td>
</tr>
<tr>
<td>DS_{lp}</td>
<td>Dual Sourcing (low margin)</td>
<td>Order quantity from each supplier</td>
</tr>
<tr>
<td>SSI_{e}</td>
<td>SSI with early commitment</td>
<td>Sole supplier, Improvement effort (if S1 is selected), Order quantity</td>
</tr>
<tr>
<td>SSI_{l}</td>
<td>SSI with late commitment</td>
<td>Improvement effort, Sole supplier, Order quantity</td>
</tr>
</tbody>
</table>
payment. With this transformation, the participants needed to exceed certain target earnings to make a positive cash earning. Any potential negative cash earnings were taken from the start-up fee paid to the participants. The average cash earnings were $24.03 and the maximum and the minimum earnings were $38.4 and 0, respectively.

5. Experimental Results

Buyers do not utilize supply risk management strategies as effectively as in theory:
We calculate the average profit (of the buyer, its suppliers and the total supply chain) for each participant and compare each treatment to the theoretical predictions using the Wilcoxon rank-sum test. Table 4 reports the results of this analysis. From this table, we conclude that the buyer’s profits under all conditions are significantly lower than predicted by standard theory. Therefore, buyers do not use risk mitigation strategies as effectively as in theory, contrary to Hypothesis 1. Participants’ deviations from theory amplify the inefficiencies in the supply chain, as evidenced by lower total supply chain profits than theory.

Examining suppliers’ profits with dual sourcing, S1’s (S2’s) profit is greater and S2’s (S1’s) profit is lower than in theory in the high (low) margin condition. The deviation from theory in profit allocation offers insights into the buyers’ ordering behavior, which will be studied in detail below. Under SSI, the participants do not utilize S1 with early and S2 with late commitment as much as in theory. We will explore the underlying supplier selection behavior in more detail below.

Buyers benefit more from SSI than dual sourcing, consistent with theory: In order to compare dual sourcing and SSI while controlling for the effects of period and variation among participants, we use a regression model. The regression equation for the buyer’s profit is given by

$$\Pi_{i,t}^{'} = \text{Intercept} + \beta_t \times t + \beta_{SSI_e} \times SSI_e + \beta_{SSI_l} \times SSI_l + \beta_{SSI_e \times t} \times (SSI_e \times t) + \beta_{SSI_l \times t} \times (SSI_l \times t) + \nu_i + \epsilon_i,t. \quad (9)$$

All other regression equations are similar.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Buyer’s Profit</th>
<th>S1’s Profit</th>
<th>S2’s Profit</th>
<th>Total Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observed</td>
<td>Obs. vs. Theory</td>
<td>Observed</td>
<td>Obs. vs. Theory</td>
</tr>
<tr>
<td>DS</td>
<td>67.97</td>
<td>Lower (p-val&lt;0.001)</td>
<td>4.4</td>
<td>Higher (p-val&lt;0.001)</td>
</tr>
<tr>
<td>SSI_e</td>
<td>73.64</td>
<td>Lower (p-val&lt;0.001)</td>
<td>8.54</td>
<td>Lower (p-val&lt;0.001)</td>
</tr>
<tr>
<td>SSI_l</td>
<td>76.42</td>
<td>Lower (p-val&lt;0.001)</td>
<td>8.45</td>
<td>Higher (p-val&lt;0.001)</td>
</tr>
<tr>
<td>DS_l</td>
<td>20.38</td>
<td>Lower (p-val&lt;0.001)</td>
<td>4.95</td>
<td>Lower (p-val&lt;0.001)</td>
</tr>
</tbody>
</table>
Here, the dependent variable is the buyer’s profit under treatment \(j\) (where \(j = 1, j = 2\) and \(j = 3\) correspond to \(DS, SSI_e\) and \(SSI_l\) described in Table 3, respectively). The independent variables \(SSI_e\) and \(SSI_l\) are dummy variables for these treatments. We capture the effect of time through an independent variable \(t\); we also account for potentially different time trends and learning behavior across treatments by including interaction terms of \(t\) with \(SSI_e\) and \(SSI_l\). We use a random-effects model to control for individual heterogeneity in the participant pool. Both error terms \(\nu_i\) and \(\epsilon_{i,t}\) follow Normal distributions with mean zero. Table 5 shows the regression coefficient estimates and their significance levels.

A direct comparison of the average performance across different treatment is not immediately available from the regression analysis because the treatment effects are represented through both direct and interaction terms. Therefore, we use linear hypothesis testing. We calculate profits averaged over period, which are defined as

\[
\pi^1 := \text{Intercept} + \beta_t \times 20, \\
\pi^2 := \text{Intercept} + \beta_t \times 20 + \beta_{SSI_e} + \beta_{SSI_e \times t} \times 20, \\
\pi^3 := \text{Intercept} + \beta_t \times 20 + \beta_{SSI_l} + \beta_{SSI_l \times t} \times 20.
\]

We then use these averages to test our hypotheses.

We find that buyer’s profits are greater with \(SSI\) than with dual sourcing, regardless of the commitment regime (p-values are 0.002 and < 0.001 for \(DS\) vs. \(SSI_e\) and \(DS\) vs. \(SSI_l\), respectively). Although the buyer’s profits under early and late commitment are comparable to each other, their comparison is directionally consistent with theoretical predictions (coefficient= 3.076, two-sided p-val:0.241). Comparison of total profits agrees with theory as well. That is, \(SSI\) increases total

Table 5  Regression coefficients for the buyer’s, suppliers’, and total supply chain profits

<table>
<thead>
<tr>
<th>Variable</th>
<th>Regression coefficient estimates and standard errors (in parentheses)</th>
<th>Total profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Buyer’s profit</td>
<td>S1’s profit</td>
</tr>
<tr>
<td>Intercept</td>
<td>68.56***</td>
<td>4.77***</td>
</tr>
<tr>
<td></td>
<td>(1.88)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>(t)</td>
<td>-0.028</td>
<td>-0.018†</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>(SSI_e)</td>
<td>3.95</td>
<td>3.21***</td>
</tr>
<tr>
<td></td>
<td>(2.67)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>(SSI_l)</td>
<td>6.3*</td>
<td>3.21***</td>
</tr>
<tr>
<td></td>
<td>(2.67)</td>
<td>(0.47)</td>
</tr>
<tr>
<td>(SSI_e \times t)</td>
<td>0.1</td>
<td>0.048***</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>(SSI_l \times t)</td>
<td>0.10</td>
<td>0.041**</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Standard deviation of (\nu_i)</td>
<td>5.83***</td>
<td>1.11***</td>
</tr>
</tbody>
</table>
profits over DS and late commitment weakly dominates early commitment (p-val= 0.09). Finally, S1 is better and S2 is worse off with supplier improvement (p-values< 0.001 for DS vs. SSI_e and DS vs. SSI_l and for both suppliers) and S2 earns higher profit with late than early commitment under SSI (p-val:0.016), consistent with theory. Therefore, Hypothesis 2 is generally supported by our experimental findings.

Buyers diversify orders more than theory with dual sourcing and use quantity hedging:
Table 6 provides a summary of the buyer’s decisions in our experiments. We take the average of each participant’s decisions in the experiment and calculate the mean and standard deviation across different individuals, and compare them to theory using the Wilcoxon rank-sum test.

Recall that in the DS treatment, the buyer is expected to order more from S2 and less from S1 (70 units from S2 vs. 40 units from S1) in standard theory. The total order quantities from the suppliers should be equal to the customer demand. In the experiments, the buyer’s order quantities from S1 and S2 are more diversified and closer to each other than suggested by theory. Therefore, the buyer orders significantly more from S1 and less from S2 than in theory, consistent with our observations about the suppliers’ profits. Moreover, buyers order significantly more than the customer demand and exhibit quantity hedging behavior. Note that quantity hedging can be theoretically optimal in supply risk management when both suppliers are risky, but is always dominated in a setting with only one risky supplier. Therefore, quantity hedging emerges as a result of the buyer’s behavioral influences in our experiments, which will be further explored in Section 6.1.

Our observations in DS_l are highly consistent: the buyer is expected to order more from S1 and less from S2 (70 units from S1 vs. 40 units from S2); however, our participants diversify their orders and buy significantly more from S2 and less from S1 than in theory. In addition, the total order quantity is significantly greater than customer demand. Interestingly, quantity hedging behavior is more pronounced in DS (average total order quantity is 128 with DS vs. 115 with DS_l), likely in order to compensate for the higher supply risk assumed by purchasing more from S1 than theory.

Buyers choose order quantity and effort decisions effectively, but may be subject to supplier selection errors with SSI: We now focus on the decisions with SSI. In Table 6, reported order quantities under the SSI treatments are conditional on S1 or S2 being chosen and “S1 choice ratio” refers to the percentage of instances that a participant chooses S1 as the sole supplier. For the late commitment treatment, we report the S1 choice ratio conditional on the

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4 Direct comparisons of the treatments using the Wilcoxon rank-sum test are qualitatively consistent with our findings described in this paragraph.

5 To confirm that this is systematic and not due to few but exceptionally large orders by some buyers, we compared theoretical predictions with order quantity decisions at the individual participant level. 9 out of 20 (10 out of 20) participants order significantly more than demand at the 5% level in the DS (DS_l) treatment.
outcome (success/failure) of the supplier improvement effort. In the second to last row, the theory prediction for S1 choice ratio is calculated conditional on the buyer’s improvement effort.

Order quantity and improvement effort decisions of human buyers tend to agree with the theoretical predictions under SSI. Even though buyers may order more than theory, the magnitude of the deviation is lower than in the dual sourcing treatments. Similarly, human buyers are relatively successful at choosing the improvement effort as the effort is not significantly different from theory. Late commitment directionally leads to higher improvement effort than early commitment (median effort across subjects are 69.12 versus 55.45) although the difference is not statistically significant (two-sided p-value: 0.72).

The main deviations from theory occur with supplier selection decisions. For example, in the SSI e treatment, buyers tend to choose S2 more frequently than theory (which predicts that S1 will be chosen with probability 1). This is even more pronounced in the SSI f treatment: buyers tend to select S1 50% of the time after observing improvement failure, even though they should select S2 in theory. Despite supplier selection errors, buyers utilize the flexibility provided by late commitment: they select S1 more often after improvement success than after failure.

6. Behavioral Models

In the previous section, we observed that behavioral inefficiencies in supply risk mitigation originated primarily from the buyer’s sourcing allocation decisions between suppliers (i.e., order allocation with dual sourcing and supplier selection in SSI). Next, we examine these inefficiencies.

6.1 Ordering Behavior in Dual Sourcing

Two key observations from the dual sourcing experiments are that (1) the buyers choose a more even order allocation between suppliers than in theory, and (2) their total order quantities are significantly greater than the customer demand, indicating quantity hedging. Now, we review alternative behavioral theories from the portfolio choice and/or OM literatures and discuss whether they can capture both of these observations. In the discussion below, we refer to the theoretical order quantities from S1 and S2 in Proposition 1 as $q_1^*$ and $q_2^*$.

Naïve diversification: In portfolio choice, Benartzi and Thaler (2001) show that when people diversify their portfolios, they do so in a naïve fashion and allocate an equal amount to each option. For our dual sourcing experiments, this translates into the buyer firm ordering the same exact amount from both suppliers. However, in only 4% of the total observations, the orders are split equally between the suppliers. Hence, our results cannot be described by naïve diversification.

Risk aversion: Our results cannot be explained by risk aversion either: The following proposition shows that a risk averse buyer would buy more from S2 and less from S1 than the solution in Proposition 1 regardless of the suppliers’ margin (contradicting our findings from DS treatment).
Table 6  Means and standard deviations (in parentheses) for the buyer’s decisions and comparison of respective decisions with theoretical predictions. Comparisons are based on the Wilcoxon rank-sum tests.  
Significance levels: (***) = 0.001, (**) = 0.01, (*) = 0.05

<table>
<thead>
<tr>
<th></th>
<th>DS</th>
<th>DS&lt;sub&gt;lp&lt;/sub&gt;</th>
<th>SSI&lt;sub&gt;e&lt;/sub&gt;</th>
<th>SSI&lt;sub&gt;i&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Theory</td>
<td>Obs.</td>
<td>Theory</td>
</tr>
<tr>
<td>q&lt;sub&gt;1&lt;/sub&gt;</td>
<td>69.38*** (27.46)</td>
<td>40</td>
<td>57.46** (23.12)</td>
<td>70</td>
</tr>
<tr>
<td>q&lt;sub&gt;2&lt;/sub&gt;</td>
<td>58.73** (16.08)</td>
<td>70</td>
<td>58.13*** (20.94)</td>
<td>40</td>
</tr>
<tr>
<td>Total Order Quantity</td>
<td>128.11*** (30.74)</td>
<td>110</td>
<td>115.585*** (9.12)</td>
<td>110</td>
</tr>
<tr>
<td>Improvement Effort</td>
<td></td>
<td></td>
<td>65.83 (28.89)</td>
<td>65.23</td>
</tr>
<tr>
<td>S1 Choice Ratio</td>
<td></td>
<td></td>
<td>0.937** (0.11)</td>
<td>1</td>
</tr>
<tr>
<td>(after success)</td>
<td></td>
<td></td>
<td>0.96** (0.06)</td>
<td>1</td>
</tr>
<tr>
<td>(after success &amp; given effort)</td>
<td></td>
<td></td>
<td>0.96 (0.06)</td>
<td>0.93</td>
</tr>
<tr>
<td>S1 Choice Ratio</td>
<td></td>
<td></td>
<td>0.50*** (0.34)</td>
<td>0</td>
</tr>
<tr>
<td>(after failure)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2  Buyers’ order quantity and effort decisions under different treatments

(a) Order quantity (DS)
(b) Order quantity (DS<sub>lp</sub>)
(c) Order quantity (SSI)
(d) Improvement effort (SSI)
Proposition 4. Consider a buyer with a continuous, twice differentiable, strictly increasing and strictly concave utility \( v(\cdot) \). With dual sourcing, the buyer’s order quantities from S1 and S2 satisfy \( q^*_{1r} \leq q^*_1 = \min\{K - G^{-1}((r - w_2)/(r - w_1)), D\} \) and \( q^*_{2r} \geq q^*_2 \).

Disutility from stockouts/leftovers: In the behavioral OM literature, Ho et al. (2010) observe that human subjects as newsvendors experience disutility from the mismatch between their stocking quantity and the observed customer demand. In particular, the subjects have psychological per-unit costs associated with stockouts and leftovers. One can suspect that similar considerations may play a role in ordering behavior under supply risks. However, the following proposition shows that stockout and/or leftover concerns cannot explain key observations from the dual sourcing experiments.

Proposition 5. Suppose that the buyer experiences disutility of \( \delta_u \) from each unmet unit of demand and \( \delta_o \) from each unit of leftover inventory.

(a) The buyer chooses the following quantities to order from S1 and S2, respectively:

\[
q^*_{1s} = \min \left\{ K - G^{-1} \left( \frac{r + \delta_u - w_2}{r + \delta_u - w_1} \right), D \right\}, q^*_{2s} = D - q^*_{1s}.
\]

(b) The buyer orders less from S1 and more from S2 than in standard theory; \( q^*_{1s} \leq q^*_1 \), \( q^*_{2s} \geq q^*_2 \).

(c) The total order quantity from both suppliers equals customer demand \( D \).

An important insight from the proof of Proposition 5 is that leftover aversion has no effect on the order quantities because the buyer’s total order quantity is equal to customer demand with standard theory (Proposition 1) and hence the buyer does not expect to have leftovers. Therefore, only stockout aversion has a direct influence on the buyer’s order quantities. Stockout aversion induces the buyer to reduce the order quantity from S1 (because that supplier may not fulfill the order due to disruptions) and increase the order quantity from S2.

Bounded rationality: Gurnani et al. (2014) find evidence for bounded rationality in ordering behavior under supply risk. In the behavioral literature on newsvendor, Su (2008) demonstrated that bounded rationality can capture the pull-to-center effect observed in inventory decisions. However, recent studies demonstrated that bounded rationality by itself cannot fully capture the observed behavior in newsvendor experiments (Kremer et al. 2010, Kalkanci and Perakis 2017). Similarly, we suspect that bounded rationality, while effective at capturing the variability in decisions, may not be the sole behavioral effect in action due to discrepancies between predicted and observed behavior: for example, in the DS treatment, a bounded rational decision making model (as described in the first column of Table 7) would predict that quantities between 70 and 75 would be ordered with the highest frequency from S2 while the mode of the observed order quantity distribution is between 55 and 60. In addition, the bounded rationality model would predict that
quantities between 60 and 65 would be ordered with the highest frequency from S1 and only 9.86% of order quantities from S1 would be at or above the customer demand. However, in reality, the mode of the observed order quantity distribution is between 45 and 50 and participants choose order quantities at or above the demand more frequently than the bounded rationality prediction (22%).\textsuperscript{6} Therefore, we conclude that there is potentially another dominant behavioral effect influencing the buyer’s utility, which would explain these systematic deviations.

**Disutility from order allocation errors:** We propose that the buyer may experience disutility from not having allocated her orders optimally between the suppliers after observing S1’s realized capacity. As a result, the buyer may choose order quantities to minimize her anticipated disutility (Bell 1982, Schweitzer and Cachon 2000). We hypothesize that the buyer tries to satisfy the customer demand from S1 as much as possible because it is cheaper, and source the remainder of customer demand from S2 given S1’s capacity shortages from disruptions. Therefore, the buyer’s disutility has two components: the disutility from not ordering the right amount from S1 after observing the available capacity, and the disutility from not ordering the right amount from S2 given S1’s delivery quantity and the customer demand. We propose that the buyer’s utility is of the form

\[
\eta(q_1, q_2|\gamma, \beta) = E \left[ \Pi(y_1(q_1), q_2) - \gamma|D - q_1|1\{K - \xi > D\} - \gamma(K - \xi - q_1)^+1\{K - \xi \leq D\} - \beta|(D - y_1(q_1))^+ - q_2| \right]
\]  

(10)

where \(\Pi(y_1(q_1), q_2)\) is defined in (1) and \(y_1(q_1) = \min\{K - \xi, q_1\}\) is the delivery quantity by S1. The first term on the right-hand side (RHS) is the buyer’s expected profit from ordering \(q_1\) and \(q_2\) from S1 and S2 respectively, and the last three terms represent the buyer’s disutility from order allocation errors. We capture the disutilities associated with the order quantities from S1 and S2 separately; \(\gamma\) and \(\beta\) are the psychological per unit costs the buyer experiences from order allocation errors related to \(q_1\) and \(q_2\), respectively.

In Equation (10), we first focus on the second and the third terms on the RHS, which capture the buyer’s disutility as a result of not ordering the right amount from S1. When S1’s realized capacity is abundant (i.e., S1’s capacity after the disruption is above the customer demand), the buyer experiences disutility from not ordering and satisfying all of the customer demand from S1. When S1’s realized capacity is tight, the buyer experiences disutility only when she underorders from S1; that is, when her order quantity is less than S1’s available capacity. In this case, the buyer does not regret overordering because a higher order quantity from S1 would have resulted in the

\textsuperscript{6}Similarly, in the low margin condition, predicted mode of the order quantity distribution from S1 (S2) is between 70 and 75 (25 and 30) while the observed mode is between 55 and 60 (45 and 50).
same exact profit while a lower order quantity would have either made no difference or led to a lower profit (by reducing S1’s delivery quantity even more).

The very last term on the RHS of Equation (10) captures the buyer’s disutility from not choosing the ex-post optimal order quantity from S2. The buyer would prefer to use S2 only when the customer demand cannot be fully satisfied by S1. Therefore, the buyer would prefer to order only the difference between the customer demand and S1’s delivery quantity and experiences ex-post disutility from not doing so.

Note that our formulation is related to prior models of reference-dependent preferences (Thaler 1985, Koszegi and Rabin 2006, Ho et al. 2010). Here, the buyer makes a multidimensional decision and each decision is compared to a reference point after observing S1’s available capacity. Specifically, the minimum of S1’s realized capacity and the customer demand serves as a reference point for the order quantity decision from S1, and the difference between the customer demand and the delivery quantity by S1 serves as a reference point for the order quantity decision from S2.

The next proposition characterizes the ordering decisions of a buyer maximizing the utility function $\eta(q_1,q_2|\gamma,\beta)$.

**Proposition 6.** The buyer’s utility-maximizing order quantities from S1 and S2 are given by:

$$(q_{1a}^*, q_{2a}^*) = \begin{cases} 
(D, \max \left\{ G^{-1}(r-\frac{w_2+\beta}{r+2\beta}) + D - K, 0 \right\} ) , & \text{if } w_1 < \gamma - \beta \\
\left( \min \left\{ K - G^{-1}(r-\frac{w_2+\beta}{r-w_1+\gamma+\beta}), D \right\} , D - q_{1a}^* \right) , & \text{if } w_1 > \gamma - \beta . \\
q_{1a}^* \in [D - q_{2a}^*, D], q_{2a}^* = \max \left\{ G^{-1}(r-\frac{w_2+\beta}{r+2\beta}) + D - K, 0 \right\} , & \text{otherwise}
\end{cases}$$

Consistent with the conditions of our experiment, we assume that $K - G^{-1}((r-w_2)/(r-w_1)) < D$ in the next corollary, which ensures that the $q_1^*$ and $q_2^*$ in Proposition 1 are interior solutions (i.e., dual sourcing is profitable).

**Corollary 1.** Suppose that $K - G^{-1}((r-w_2)/(r-w_1)) < D$.

(a) The buyer’s utility-maximizing order quantity from S1 is strictly greater and from S2 is strictly less than predicted by standard theory in Proposition 1 if and only if

$$w_1 > \gamma - \beta \text{ and } \frac{r-w_2}{r-w_1} > \frac{\beta}{\gamma + \beta} \text{ or } w_1 \leq \gamma - \beta \text{ and } \frac{r-2w_2+w_1}{w_1(r-w_2)} > -\frac{1}{\beta}.$$ 

The buyer’s utility-maximizing order quantity from S1 is strictly less and from S2 is strictly greater than predicted by standard theory if \(w_1 > \gamma - \beta \text{ and } (r-w_2)(r-w_1) < \beta/(\gamma + \beta)).

(b) The buyer’s total order quantity from both suppliers is strictly greater than the customer demand $D$ if $w_1 < \gamma - \beta$ and $G^{-1}((r-w_2+\beta)/(r+2\beta)) + D - K > 0$. 

The proposed model is qualitatively consistent with important aspects of the observed behavior in our experiments. First, depending on the buyer’s relative margin from the suppliers, the buyer may choose a higher or a lower allocation of orders from S1 than standard theory (Corollary 1(a)). For example, suppose that \( w_1 \) is above \( \gamma - \beta \). In the high margin condition where the buyer’s margins from both suppliers, and hence, the buyer’s relative margin from S2 is high, behavioral model predicts a higher allocation of orders from S1 than theory. In the low margin condition, we expect to observe the opposite. Second, the buyer may exhibit quantity hedging behavior and order more than the customer demand depending on the magnitudes of her individual \( \gamma \) and \( \beta \) parameters (Corollary 1(b)). This is more likely to occur under a sufficiently low wholesale price (consistent with the more pronounced overordering behavior in the DS treatment). Finally, if the buyer’s psychological cost of not ordering the right amount from the cheap supplier is sufficiently high, the buyer may order the customer demand fully from the cheap but risky supplier S1 and use the reliable supplier completely as a back-up option. This helps to explain many occurrences in which participants’ order quantities from S1 are in the vicinity of the customer demand.

**Estimation:** We use maximum likelihood estimation to estimate the parameters of this model at the population level using our full dataset from the dual sourcing treatments. We assume that the buyer chooses order quantities to maximize (10) but may exhibit random variations from the expected-utility maximizing behavior due to bounded rationality. Therefore, the likelihood function is given by

\[
LLK = \prod_{c \in \{h, l\}} \prod_i \prod_t \exp(\lambda_c \eta(q_{1,c,i,t}, q_{2,c,i,t} | \gamma, \beta, w_{1,c}, w_{2,c})) / \sum_{q_1=0}^{K} \sum_{q_2=0}^{K} \exp(\lambda_c \eta(q_1, q_2 | \gamma, \beta, w_{1,c}, w_{2,c})).
\]  

(11)

Here, \( c \) denotes the treatment (low or high margin condition), \( i \) is the index for participants, \( t \) is the index for period in the experiment, \( q_{1,c,i,t} \) and \( q_{2,c,i,t} \) represent the order quantities from S1 and S2. \( \lambda_c \) is the bounded rationality parameter that represents the decision maker’s propensity to select the expected-utility maximizing order quantities from S1 and S2. If \( \lambda_c = 0 \), the decision maker chooses the order quantities fully randomly. As \( \lambda_c \) approaches infinity, the decision maker chooses the expected utility-maximizing order quantities from S1 and S2 with probability 1. We specify the psychological unit costs \( \gamma \) and \( \beta \) to be common across the two treatments because all participants presumably are subject to these costs. We estimate the bounded rationality parameter separately for each treatment to account for differences in decision variability across treatments.

Table 7 shows the parameter estimates and significance levels. The figures in parentheses are standard errors clustered at the participant level to account for within-subject correlation in the order quantities. The first and last columns provide the estimates of the model with bounded rationality only and the full model, respectively. All behavioral model parameters are significant in
### Table 7  Estimation results. Robust standard errors are provided in parentheses. Significance levels are measured by t-tests. Significance levels: (*** = 0.001, (**) = 0.01, (*) = 0.05)

<table>
<thead>
<tr>
<th>Estimated Parameters</th>
<th>Bounded Rationality</th>
<th>Disutility from Errors &amp; Bounded Rationality ($\gamma = \beta$)</th>
<th>Disutility from Errors &amp; Bounded Rationality (full model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>-</td>
<td>0.366***</td>
<td>0.487*</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-</td>
<td>(0.1)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>$\lambda_h$</td>
<td>0.311***</td>
<td>0.366***</td>
<td>0.923*</td>
</tr>
<tr>
<td>($\lambda_l$</td>
<td>-</td>
<td>(0.1)</td>
<td>(0.402)</td>
</tr>
<tr>
<td>$\lambda_l$</td>
<td>0.379***</td>
<td>0.188***</td>
<td>0.122***</td>
</tr>
<tr>
<td>($\beta_l$</td>
<td>(0.098)</td>
<td>(0.064)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>$\gamma_l$</td>
<td>0.379***</td>
<td>0.287***</td>
<td>0.23***</td>
</tr>
<tr>
<td>($\beta_l$</td>
<td>(0.16)</td>
<td>(0.130)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>-LLK</td>
<td>13857.272</td>
<td>13556.994</td>
<td>13139.974</td>
</tr>
</tbody>
</table>

Wald test and p-value
(test against the full model)

$\chi^2(2) = 216.44$  $\chi^2(1) = 160.34$

p-value < 0.001  p-value < 0.001

### Table 8  Behavioral model versus standard theory predictions

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Order Quantity</th>
<th>Behavioral Model (BM) Prediction</th>
<th>Standard Theory (ST) Prediction</th>
<th>Difference (Observed-BM)</th>
<th>Difference (Observed-ST)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High margin</td>
<td>$q_1$</td>
<td>69.38</td>
<td>64.42</td>
<td>40</td>
<td>4.96</td>
</tr>
<tr>
<td></td>
<td>$q_2$</td>
<td>58.73</td>
<td>66.09</td>
<td>70</td>
<td>-7.36</td>
</tr>
<tr>
<td>Low margin</td>
<td>$q_1$</td>
<td>57.46</td>
<td>57.40</td>
<td>70</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>$q_2$</td>
<td>58.13</td>
<td>58.26</td>
<td>40</td>
<td>-0.13</td>
</tr>
</tbody>
</table>

both models. We observe from the results of the Wald test that the full behavioral model captures the experimental observations significantly better than bounded rationality only model.\(^7\) Therefore, our model is supported empirically.

We also estimate a special case of the full model where $\gamma$ and $\beta$ are constrained to be equal to gain insights on $\gamma$ and $\beta$ parameters. Wald test results demonstrate that allowing $\gamma$ and $\beta$ to be different significantly improves the descriptive power of the model. In the full model, the magnitude of the $\beta$ estimate is greater than $\gamma$. This implies that the buyers experience higher disutility related to errors in ordering from S2 since this supplier is more expensive.

We use the estimates of the behavioral model parameters to predict the buyer’s order quantities from the suppliers and compare them with the observed average order quantities in Table 8. The table shows that predictions of the behavioral model follow observations much more closely than standard theory. Therefore, enriching theoretical models of dual sourcing with the behavioral influences on the participants’ decision making will substantially increase their predictive power.

#### 6.2 Supplier Selection Behavior in SSI

In this section, we delve into the behavioral drivers of supplier selection for sole sourcing under SSI. Deviations in supplier selection cannot systematically be explained by risk considerations because the buyers tend to select the reliable supplier more often than theory with early commitment while they select the risky supplier more often than theory after failure with late commitment.

\(^7\) As in Ho et al. (2010), we use Wald test instead of likelihood ratio test due to the dependence of observations from the same participant in our data.
We formulate a bounded rationality model to capture the buyer’s supplier selection decision. Below, we make the simplifying assumption that the order quantity exactly equals customer demand $D$ regardless of the selected supplier and suppress quantity decisions in the formulations.

**Estimation:** With early commitment, if S1 is chosen, the buyer anticipates choosing the expected profit maximizing improvement effort decision (which is supported by the empirical evidence in Section 5). The buyer’s expected profit upon choosing S1 and S2 are $\Psi_1$ (given by (3)) and $\psi_2$ (given by (6)), respectively. In our estimations, we maximize the likelihood function calculated as

$$\prod_i \prod_t \left\{ \left( \frac{\exp(\lambda \Psi_1)}{\exp(\lambda \Psi_1) + \exp(\lambda \psi_2)} I(s_{i,t} = 1) \phi((z_{i,t} - z^*)/\sigma) + \frac{\exp(\lambda \psi_2)}{\exp(\lambda \Psi_1) + \exp(\lambda \psi_2)} I(s_{i,t} = 2) \right) \right\}. $$

Here, $z_{i,t}$ and $s_{i,t} \in \{1, 2\}$ are the effort and supplier choices of participant $i$ at period $t$ in the experiment respectively, $z^*$ is the optimal improvement effort (from Proposition 3(a)) and $\lambda$ is the bounded rationality parameter. The error for the improvement effort decision is Normally distributed with zero mean and variance $\sigma^2$ and $\phi(\cdot)$ is the standard Normal distribution density.

With late commitment, we propose a behavioral model similar to above, but with two notable differences: first, the buyer observes the improvement outcome and factors that in calculating the expected profit from the risky supplier. Second, the buyer makes the effort choice before committing to a supplier, and hence, incorporates subsequent supplier selection behavior in making the improvement effort decision$^8$. Hence, we maximize the likelihood function calculated as

$$\prod_i \prod_t \left\{ \left( \frac{\exp(\lambda \psi_{1,n}(z))}{\exp(\lambda \psi_{1,n}) + \exp(\lambda \psi_2)} I(o_{i,t} = 0) + \frac{\exp(\lambda \psi_{1,s}(z_{i,t}))}{\exp(\lambda \psi_{1,s}(z_{i,t})) + \exp(\lambda \psi_2)} I(o_{i,t} = 1) \right) I(s_{i,t} = 1) \right\} \left( \frac{\exp(\lambda \psi_2)}{\exp(\lambda \psi_{1,n}) + \exp(\lambda \psi_2)} I(o_{i,t} = 0) + \frac{\exp(\lambda \psi_2)}{\exp(\lambda \psi_{1,s}(z_{i,t})) + \exp(\lambda \psi_2)} I(o_{i,t} = 1) \right) I(s_{i,t} = 2) \phi((z_{i,t} - z^*_i)/\sigma) $$

(12)

Here, $o_{i,t} \in \{0, 1\}$ is the outcome of improvement effort, $s_{i,t} \in \{1, 2\}$ is the supplier choice, and $z_{i,t}$ is the effort decision of participant $i$ at period $t$ in the experiment. $\psi_{1,s}(\cdot)$ and $\psi_{1,n}(\cdot)$ are the buyer’s expected profits by sourcing from S1 after improvement success and failure, respectively; they are defined in (4) and (5). $z^*_i$ is the buyer’s expected profit-maximizing improvement effort given random errors in supplier selection; i.e.,

$$z^*_i = \max_{z \geq 0} \left\{ \theta \left( \frac{\exp(\lambda \psi_{1,s}(z))}{\exp(\lambda \psi_{1,s}(z)) + \exp(\lambda \psi_2)} \psi_{1,s}(z) + \frac{\exp(\lambda \psi_2)}{\exp(\lambda \psi_{1,s}(z)) + \exp(\lambda \psi_2)} \psi_{1,n}(z) \right) 
+ (1 - \theta) \left( \frac{\exp(\lambda \psi_{1,n})}{\exp(\lambda \psi_{1,n}) + \exp(\lambda \psi_2)} \psi_{1,n} + \frac{\exp(\lambda \psi_2)}{\exp(\lambda \psi_{1,n}) + \exp(\lambda \psi_2)} \psi_{1,n} \right) - mz \right\} $$

$^8$ We have also considered an alternative formulation where the buyer’s effort decision is assumed to equal the standard theory prediction plus a Normally distributed error term and where supplier selection errors are captured as in (12). This alternative formulation is dominated by the proposed formulation, leading to a lower likelihood.
The error for the improvement effort decision is Normally distributed with zero mean and variance $\sigma^2$ in (12) and $\lambda$ is bounded rationality parameter.

We use maximum likelihood estimation to find $\lambda$ and $\sigma$ estimates with early and late commitment. Table 9 shows the parameter estimates and significance levels. The figures in parentheses are standard errors clustered at the subject level to account for within-subject correlation in the order quantities. As observed from the table, estimates of the behavioral model parameters are highly significant. By applying the Wald test, we find support for the full behavioral models under both commitment strategies at the 0.1% level.

**Implications of supplier selection errors:** An important observation from the behavioral model is that supplier selection errors under late commitment can lead the buyer to exert greater improvement effort than predicted by standard theory (Figure 3). This is because random supplier selection errors *increase the marginal value* of the improvement effort: in the presence of random errors, the improvement effort increases both the potential expected profit from the risky supplier and the probability of selecting that supplier. Supplier selection errors do not have the same effect for early commitment because the buyer chooses the improvement effort after selecting the supplier. Directionally, behavioral model prediction is consistent with the deviation of the average improvement effort with late commitment from standard theory and from the effort with early commitment.

**Figure 3** Expected profit-maximizing improvement effort with late commitment in the presence of supplier selection errors as a function of $\lambda$. Dashed line demonstrates the standard theory prediction.
Consequently, in contrast to Proposition 3(b), late commitment can lead to greater improvement effort than early commitment when supplier selection errors are considered.

7. Conclusion

In this paper, we study two sourcing strategies to mitigate supply risks. These strategies require different levels of buyer involvement to eliminate risks: dual sourcing is an indirect risk management strategy in which the buyer considers risk and cost profiles of suppliers as given and tries to balance the trade-off between cost and supply risk by balancing order quantity decisions between suppliers. With SSI, on the other hand, the buyer can directly influence the suppliers’ risk profile by exerting costly effort. Our study serves two purposes: (1) we test the efficacy of these two sourcing strategies to mitigate supply risks and identify behavioral drivers of inefficiencies observed in experiments, (2) we test the theoretical prediction that SSI can be more effective than dual sourcing under high cost heterogeneity between the suppliers.

Our results demonstrate the relative efficacy of direct risk mitigation through supplier improvement over indirect risk mitigation through dual sourcing: SSI leads to both higher buyer and supply chain profits than dual sourcing, consistent with standard theory predictions for our setting. Moreover, buyers (as well as the supply chain) tend to benefit from maintaining a flexible supplier base while pursuing improvement opportunities, as demonstrated by the relative success of the late sourcing commitment in experiments. The buyers are relatively successful in evaluating the supply risk versus the improvement cost trade-off in choosing their effort to improve a supplier, as their effort decisions are comparable to theory. However, across all treatments, behavioral inefficiencies originate primarily from the buyer’s sourcing allocation decisions between suppliers, namely, supplier selection for sole sourcing in SSI and order allocation with dual sourcing.

With dual sourcing, buyers allocate order quantities more evenly between suppliers than predicted by theory. Additionally, participants may hedge against the supply risk by artificially inflating their order quantity above the customer demand (i.e., use quantity hedging). We propose and empirically validate a theory of order allocation error minimization to explain these observations: buyers experience disutility from not having allocated the orders optimally between suppliers after observing the impact of a disruption on a supplier’s available capacity. This model provides insights into why devising a proactive supply risk management strategy is very difficult: even if the buyer chooses an order allocation to proactively account for sourcing risks, the buyer may experience disutility afterwards from not sourcing more from the cheaper supplier if that supplier is not hit heavily by disruptions. This is fully aligned with Zsidisin et al. (2000)’s observation that managers find it difficult to justify resources spent for risk management if a risk never materializes.

Under SSI, main deviations from theory occur in supplier selection decisions. Note that these decisions are strategic and often require managerial input in practice. We propose and empirically
validate that bounded rationality can contribute to supplier selection errors. The implication of this observed behavior is that buyers may have difficulty in combining multiple dimensions of supplier performance (such as disruption risk and cost in our experiments) to accurately compare different sourcing options. Therefore, decision support tools that can combine multiple dimensions of supplier performance and make meaningful comparisons between different sourcing strategies will be particularly valuable.

Our study also has certain limitations. Turning to the lab to compare different risk mitigation strategies is the natural approach since detailed information on supplier performance and problems is often not shared publicly and researchers are only beginning to obtain large scale empirical data on supply disruptions. As data availability is improved, it will be possible to conduct empirical studies that compare different supply risk mitigation strategies. Another potential limitation is that we have conducted our experiments with student participants. Behavioral OM literature documents that managers make consistent decisions with student subjects in newsvendor ordering (Bolton et al. 2012); how managers make sourcing decisions in an incentive-aligned environment like ours facing supply risks will be an interesting and important extension of our research.

Another important avenue for future research is about how to counter the behavioral biases to improve decision making on supply risks in practice. For example, identifying mechanisms through which psychological costs of order allocation errors can be reduced and/or completely eliminated in dual sourcing will be a particularly important path for future research.

Acknowledgments
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References


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Online Companion

EC.1. Proofs of the Analytical Results

Proof of Proposition 1: Let \( q_1 \) and \( q_2 \) represent the order quantities from S1 and S2 respectively. The buyer’s optimization problem is \( \max_{0 \leq q_1, q_2 \leq K} \Pi(y_1(q_1), q_2) \) with

\[
\Pi(y_1(q_1), q_2) = E[-w_1y_1(q_1) - w_2q_2 + r \min\{D, y_1(q_1) + q_2\}]
\]

\[
= E[(r - w_1)y_1(q_1) + (r - w_2)q_2 - r(y_1(q_1) + q_2 - D)^+] 
\]

(EC.1)

wherein the expectation is with respect to \( \xi \) and \( y_1(q_1) \) is the quantity received from S1 given by (2). Let \( q_1^* \) and \( q_2^* \) represent the equilibrium order quantities of the buyer firm from S1 and S2 respectively; \( (q_1^*, q_2^*) \in \arg \max_{q_1, q_2 \geq 0} \Pi(y_1(q_1), q_2) \). It must be that \( q_2^* \leq D \) because for any \( q_2 > D \), \( \partial \Pi(y_1(q_1), q_2)/\partial q_2 = -w_2 < 0 \) by (EC.1). \( y_1(q_1) \geq 0 \) and \( w_2 > 0 \). Moreover, the equilibrium quantities should satisfy \( q_1^* + q_2^* - D \geq 0 \); otherwise, \( y_1(q_1^*) + q_2^* - D < q_1^* + q_2^* - D \) for all realizations of \( \xi \) by (2), and \( \partial \Pi(y_1(q_1^*), q_2^*)/\partial q_2 = r - w_2 > 0 \) by our initial assumption that \( w_2 < r \). This means that the buyer can strictly increase the expected profit by increasing \( q_2^* \), contradicting its optimality. Finally, for any \( \hat{q}_2 \leq D \) and \( D - \hat{q}_2 < \hat{q}_1 \leq K \) (for which \( \hat{q}_1 + \hat{q}_2 - D > 0 \)) we have \( \Pi(y_1(D - \hat{q}_2), \hat{q}_2) > \Pi(y_1(\hat{q}_1), \hat{q}_2) \) because \( \partial \Pi(y_1(\hat{q}_1), \hat{q}_2)/\partial q_1 < 0 \) for \( \hat{q}_1 \in (D - \hat{q}_2, K) \), \( \partial \Pi(y_1(\hat{q}_1), \hat{q}_2)/\partial q_1 = 0 \) at \( \hat{q}_1 = K \), and \( \Pi(y(\hat{q}_1), \hat{q}_2) \) is continuous (due to the continuity of \( G(\cdot) \)). Therefore, \( q_1^* + q_2^* - D = 0 \).

In the rest of the analysis, we restrict our attention to \((q_1, q_2)\) such that \( q_1 + q_2 - D = 0 \) and \( 0 \leq q_2 \leq D \). Substituting \( D - q_1 \) for \( q_2 \), the buyer’s problem can be rewritten as follows:

\[
\max_{0 \leq q_1 \leq D} \Pi(y_1(q_1), D - q_1) = \max_{0 \leq q_1 \leq D} E[(r - w_1) \min\{q_1, K - \xi\} + (r - w_2)(D - q_1)].
\]

The first-order condition for \( q_1 \) is \( G(K - q_1^*) = (r - w_2)/(r - w_1) \) (and is sufficient since the buyer’s objective is strictly concave), and consequently, \( q_1^* = \min\{K - G^{-1}((r - w_2)/(r - w_1)), D\} \) and \( q_2^* = D - q_1^* \).

Proof of Proposition 2: For both early and late commitment, the buyer chooses the order quantity after making the supplier choice and observing the success/failure of the improvement effort (if it is undertaken). Therefore, we consider the buyer firm’s order quantity choice under three contingencies: when S1 is selected and improvement efforts are successful, when S1 is selected and improvement efforts fail, and when S2 is selected. S2 is not subject to any disruption risk and the demand is deterministic, it follows from (6) that the optimal order quantity is \( D \). Now, we consider the optimal order quantity when S1 is selected. If the improvement effort is successful, the buyer determines the optimal order quantity (given the improvement effort \( z \) chosen earlier) according to \( \max_{0 \leq q_1 \leq K} \psi_{1,s}(z, q_1) \) with \( \psi_{1,s}(z, q_1) \) defined as in (4). The derivative of \( \psi_{1,s}(z, q_1) \)
with respect to \( q_1 \) is \( d\psi_{1,s}(z,q_1)/dq_1 = (r - w_1)G_s(K - q_1, a(z)) \) for \( q_1 \leq D \) and \(-w_1 \) for \( q_1 > D \). The derivative is strictly negative for \( q_1 > D \) because \( w_1 > 0 \), and the derivative is strictly positive for \( q_1 \leq D \) because \( r > w_1 \), \( q_1 \leq D < K \) and the lower bound of the support of \( \xi_s \) is 0. Therefore, the buyer’s objective function is strictly increasing for \( q_1 \in [0, D] \) and strictly decreasing for \( q_1 \in (D, K] \) and the function is continuous (due to the continuity of \( G_s(\cdot, a(z)) \)). Therefore, the optimal order quantity is \( D \). The case with improvement failure follows from the analysis under improvement success because of its equivalence to a case with \( z = 0 \).

**Proof of Proposition 3:** (a.) We consider the buyer’s effort selection problem (3) upon choosing to source from S1. From Proposition 2, the buyer orders \( D \) after observing the improvement success/failure and therefore,

\[
\max_{0 \leq q_1 \leq K} \psi_{1,s}(z,q_1) = \psi_{1,s}(z,D) = E_{\xi_s}[(r - w_1)\min\{D, K - \xi_s\}|a(z)],
\]

\[
\max_{0 \leq q_1 \leq K} \psi_{1,n}(q_1) = \psi_{1,n}(D) = E_{\xi_s}[(r - w_1)\min\{D, K - \xi\}].
\]

The buyer’s expected profit maximization problem (3) for selecting the optimal effort \( z \) can be updated using the two expressions above. Taking the first-order conditions with respect to \( z \), and noting that \( E_{\xi_s}[(r - w_1)\min\{D, K - \xi_s\}|a(z)] = (r - w_1)\int_{K-D}^{K} G_s(x,a(z))dx \) (by Lemma D.1 in Porteus 2002), we obtain condition (8) in the statement of the Proposition. Moreover, the second derivative of the buyer’s objective function equals

\[
\theta(r - w_1) \int_{K-D}^{K} \left( \frac{\partial^2 G_s(x,a(z))}{\partial a^2} a'(z) + \frac{\partial G_s(x,a(z))}{\partial a} a''(z) \right) dx,
\]

which is nonpositive for any \( z \) by our assumptions \( \frac{\partial^2 G_s(x,a(z))}{\partial a^2} \leq 0 \), \( a'(z) > 0 \), \( a''(z) \leq 0 \), and \( \frac{\partial G_s(x,a(z))}{\partial a} \geq 0 \). Hence, the buyer’s objective function is concave and the first-order condition is sufficient.

(b.) By Proposition 2, the buyer’s objective function for effort selection with early commitment to S1 (3) can be rewritten as \( \Pi_1'(z) = \theta \psi_{1,s}(z,D) + (1 - \theta)\psi_{1,n}(D) - mz \) and the buyer’s objective function for effort selection with late commitment (7) equals \( \Pi_1'(z) = \theta \max\{\psi_{1,s}(z,D), \psi_{2}(D)\} + (1 - \theta)\max\{\psi_{1,n}(D), \psi_{2}(D)\} - mz \). Note that \( d\psi_{2}(D)/dz = 0 \) (i.e., improvement effort does not increase the buyer’s expected profit if S2 is selected later). Therefore, \( \frac{d\Pi_1'(z)}{dz} \leq \theta \frac{d\psi_{1,s}(z,D)}{dz} - m = \frac{d\Pi_1'(z)}{dz} \). As shown in (a.), the buyer’s objective with early commitment is concave. We consider two cases: (i) if the objective is strictly concave, \( z^* \), the optimal effort under early commitment to S1, is unique and \( \frac{d\Pi_1'(z)}{dz} < 0 \) for \( z > z^* \). Hence, \( \frac{d\Pi_1'(z)}{dz} < 0 \) for \( z > z^* \) and the optimal effort with late commitment should be less than or equal to \( z^* \). (ii) If the buyer’s objective is concave, let \( z^* \) be the supremum of the set of optimal effort values under early commitment to S1. Then, \( \frac{d\Pi_1'(z)}{dz} < 0 \)
for \( z > z^* \) and \( \frac{dN_1(z)}{dz} < 0 \) for \( z > z^* \), which implies that the supremum of the set of optimal effort values with late commitment should be less than or equal to \( z^* \).

(c.) Denoting the buyer’s optimal effort under early commitment to S1 with \( z^* \), we observe that the buyer’s expected profit with late commitment is weakly greater than the buyer’s expected profit when S2 is chosen in early commitment; i.e.,

\[
\max_{z \geq 0} \{ \theta \max\{\psi_{1,s}(z, D), \psi_{2}(D)\} + (1 - \theta) \max\{\psi_{1,n}(D), \psi_{2}(D)\} - mz \}
\geq \theta \max\{\psi_{1,s}(z^*, D), \psi_{2}(D)\} + (1 - \theta) \max\{\psi_{1,n}(D), \psi_{2}(D)\} - mz^*
\geq \theta \psi_{1,s}(z^*, D) + (1 - \theta)\psi_{1,n}(D) - mz^* = \Psi_1,
\]

(EC.2)

where the first inequality above is by maximization of the buyer’s objective with late commitment. By similar reasoning, we also observe that the buyer’s expected profit with late commitment is weakly greater than the buyer’s expected profit when S2 is chosen in early commitment;

\[
\max_{z \geq 0} \{ \theta \max\{\psi_{1,s}(z, D), \psi_{2}(D)\} + (1 - \theta) \max\{\psi_{1,n}(D), \psi_{2}(D)\} - mz \}
\geq \theta \max\{\psi_{1,s}(0, D), \psi_{2}(D)\} + (1 - \theta) \max\{\psi_{1,n}(D), \psi_{2}(D)\} \geq \psi_{2}(D).
\]

(EC.3)

By (EC.2) and (EC.3), we have \( \max_{z \geq 0} \{ \theta \max\{\psi_{1,s}(z, D), \psi_{2}(D)\} + (1 - \theta) \max\{\psi_{1,n}(D), \psi_{2}(D)\} - mz \} \geq \max\{\Psi_1, \psi_{2}(D)\} \), which is equal to the statement of the Proposition.

**Proof of Proposition 4:** Representing the order quantities from S1 and S2 with \( q_1 \) and \( q_2 \) respectively, the buyer’s optimization problem is \( \max_{0 \leq q_1, q_2 \leq K} \nu(y_1(q_1), q_2) \) with

\[
\nu(y_1(q_1), q_2) = E[v((r - w_1)y_1(q_1) + (r - w_2)q_2 + r(y_1(q_1) + q_2 - D)^+)]
\]

wherein the expectation is with respect to \( \xi \) and \( y_1(q_1) = \min\{q_1, (K - \xi)\} \) as in Proposition 1. Let \( q_1^* \) and \( q_2^* \) represent the equilibrium order quantities of the buyer firm from S1 and S2, respectively. First, our analysis in Proposition 1 can be extended in a straightforward manner to show that \( q_2^* \leq D \) and \( q_1^* + q_2^* - D = 0 \) (because \( v(\cdot) \) is strictly increasing and continuous). Therefore, we restrict our attention to \((q_1, q_2)\) such that \( q_1 + q_2 - D = 0 \) and \( 0 \leq q_2 \leq D \). Substituting \( D - q_1 \) for \( q_2 \), the buyer’s problem can be rewritten as follows:

\[
\max_{0 \leq q_1 \leq D} \nu(y_1(q_1), D - q_1) = E[v((r - w_1)\min\{q_1, K - \xi\} + (r - w_2)(D - q_1))].
\]

(EC.4)

Let \( \tilde{q}_1 \) be the solution to the first-order condition of the buyer’s problem when the buyer is risk neutral (i.e., when \( v(x) = x \)). \( \tilde{q}_1 \) satisfies

\[
\int_0^{K - \tilde{q}_1} (w_2 - w_1)g(\xi)d\xi - \int_{K - \tilde{q}_1}^K (r - w_2)g(\xi)d\xi = 0
\]

(EC.5)
or equivalently, \( \tilde{q}_1 = K - G^{-1}((r - w_2)/(r - w_1)) \). Evaluating the first derivative of the objective (EC.4) at \( \tilde{q}_1 \), we observe that

\[
\int_0^{K-\tilde{q}_1} v'((r - w_1)\tilde{q}_1 + (r - w_2)(D - \tilde{q}_1))(w_2 - w_1)g(\xi)d\xi - \int_{K-\tilde{q}_1}^{K} v'((r - w_1)(K - \xi) + (r - w_2)(D - \tilde{q}_1))(r - w_2)g(\xi)d\xi < 0,
\]

where the inequality is by \( r > w_2 > w_1 \), (EC.5), \( v'() > 0 \), and the fact that \( v'((r - w_1)\tilde{q}_1 + (r - w_2)(D - \tilde{q}_1)) < v'((r - w_1)(K - \xi) + (r - w_2)(D - \tilde{q}_1)) \) for \( \xi > K - \tilde{q}_1 \) (because \( v''() < 0 \)). Moreover, the second derivative of the buyer’s objective function (EC.4) equals \( \int_0^{K-\tilde{q}_1} v''((r - w_1)q_1 + (r - w_2)(D - q_1))(w_2 - w_1)^2g(\xi)d\xi + \int_{K-\tilde{q}_1}^{K} v''((r - w_1)(K - \xi) + (r - w_2)(D - q_1))(r - w_2)^2g(\xi)d\xi - v'((r - w_1)\tilde{q}_1 + (r - w_2)(D - \tilde{q}_1))(r - w_2)g(D - q_1) \) and is strictly negative for all \( q_1 \in [0, K] \) because \( v''() < 0 \), \( r > w_2 > w_1 \), \( v'() > 0 \), and \( g(\xi) > 0 \) for \( \xi \in [0, K] \). Therefore, the buyer’s objective is strictly concave and the solution to the first-order conditions of the buyer’s problem, \( \tilde{q}_{1r} \), must satisfy \( \tilde{q}_{1r} < \tilde{q}_1 \). The optimal order quantities when the buyer is risk averse are \( q_{1r}^* = \min(\tilde{q}_{1r}, D) \) and \( q_{2r}^* = D - q_{1r}^* \). Consequently, \( q_{1r}^* = \min(\tilde{q}_{1r}, D) \leq \min(\tilde{q}_1, D) = q_1^* \) and \( q_{2r}^* = D - q_{1r}^* \geq D - q_1^* = q_2^* \) where \( q_1^* \) and \( q_2^* \) are the optimal order quantities when the buyer is risk neutral as identified in Proposition 1.

**Proof of Proposition 5:** (a) The buyer’s expected utility maximization problem is given by

\[
\max_{0 \leq q_1, q_2 \leq K} E \left[ \Pi(y_1(q_1), q_2) - \delta_u(D - y_1(q_1) - q_2)^+ - \delta_o(y_1(q_1) + q_2 - D)^+ \right] = \max_{0 \leq q_1, q_2 \leq K} E \left[ r \min\{D, y_1(q_1) + q_2\} - w_1 y_1(q_1) - w_2 q_2 - \delta_u(D - y_1(q_1) - q_2)^+ - \delta_o(y_1(q_1) + q_2 - D)^+ \right].
\]

Note that \( (D - y_1(q_1) - q_2)^+ = D - \min\{D, y_1(q_1) + q_2\} \) and \( (y_1(q_1) + q_2 - D)^+ = y_1(q_1) + q_2 - \min\{D, y_1(q_1) + q_2\} \), and therefore, the buyer’s objective can be written as

\[
\max_{0 \leq q_1, q_2 \leq K} E \left[ -\delta_u D - (w_1 + \delta_o)y_1(q_1) - (w_2 + \delta_o)q_2 + (r + \delta_u + \delta_o)\min\{D, y_1(q_1) + q_2\} \right].
\]

\( \delta_u D \) is a constant and can be ignored. The rest of the expression is equivalent to the buyer’s objective when the buyer does not have stock-out/leftover concerns, the market price is equal to \( \tilde{r} = r + \delta_u + \delta_o \), and the suppliers’ wholesale prices are \( \tilde{w}_1 = w_1 + \delta_u \), and \( \tilde{w}_2 = w_2 + \delta_o \). Therefore, the optimal solution can be characterized as in Proposition 1, by replacing \( r \) with \( \tilde{r} \), \( w_1 \) with \( \tilde{w}_1 \) and \( w_2 \) with \( \tilde{w}_2 \). The optimal order quantity from S1 equals \( q_{1s}^* = \min\{K - G^{-1}((r + \delta_u - w_2)/(r + \delta_u - w_1)), D\} \) and the optimal order quantity from S2 equals \( q_{2s}^* = D - q_{1s}^* \).

(b) Since \( (r + \delta_u - w_2)/(r + \delta_u - w_1) \) is strictly increasing with \( \delta_u \) (which can be verified with differentiation and noting that \( w_2 > w_1 \)), the optimal order quantity from S1 is lower and from S2 is greater than the respective order quantities specified in Proposition 1.
(c) This part immediately follows from (a).

Proof of Proposition 6: Let \( q_1 \) and \( q_2 \) represent the order quantities from S1 and S2, respectively. The buyer’s optimization problem is \( \max_{q_1, q_2} \eta(q_1, q_2) \) with

\[
\eta(q_1, q_2) = E[(r - w_1)y_1(q_1) + (r - w_2)q_2 - r(y_1(q_1) + q_2 - D)]^+ - \gamma \left[ D - \min\{K - \xi, D\} - q_1 \right] - \beta \left[ (D - y_1(q_1))^+ - q_2 \right],
\]

(EC.6)

wherein the expectation is with respect to \( \xi \) and \( y_1(q_1) \) is the quantity received from S1 given by (2). Let \( q_{1a}^* \) and \( q_{2a}^* \) represent the equilibrium order quantities of the buyer firm from S1 and S2 respectively; \( (q_{1a}^*, q_{2a}^*) \in \arg \max_{q_1, q_2} \eta(q_1, q_2) \). It must be that \( q_{2a}^* \leq D \) because for any \( q_2 > D \), \( \partial \eta(q_1, q_2)/\partial q_2 = -w_2 - \beta < 0 \) by (EC.6), \( y_1(q_1) \geq 0, w_2 > 0 \) and \( \beta \geq 0 \). Moreover, the equilibrium quantities should satisfy \( q_{1a}^* + q_{2a}^* - D \geq 0 \); otherwise, \( y_1(q_{1a}^*) + q_{2a}^* - D \leq q_{1a}^* + q_{2a}^* - D < 0 \) for all realizations of \( \xi \) by (2), and \( \partial \eta(q_{1a}^*, q_{2a}^*)/\partial q_2 = r - w_2 + \beta > 0 \) by our initial assumption that \( w_2 < r \) and \( \beta \geq 0 \). It must also be that \( q_{1a}^* \leq D \) because for any \( q_1 > D \) and \( q_1 < K \), \( \partial \eta(q_1, q_2)/\partial q_1 = -G(K - q_1)(w_1 + \gamma) - (G(K - D) - G(K - q_1))\gamma < 0 \) by \( w_1 > 0 \) and \( \gamma \geq 0 \), and \( \partial \eta(q_1, q_2)/\partial q_1 \leq 0 \) at \( q_1 = K \). Since \( \eta(q_1, q_2) \) is continuous with respect to \( q_1 \) (due to the continuity of \( G(\cdot) \)), \( \eta(D, q_2) > \eta(q_1, q_2) \) for \( q_1 > D \). Hence, \( q_{1a}^* \leq D \).

In the rest of the analysis, we restrict our attention to \( q_1, q_2 \leq D \) and \( q_1 + q_2 - D \geq 0 \). In this region, \( \eta(q_1, q_2) \) can be rewritten as

\[
\eta(q_1, q_2) = E[(r - w_1)y_1(q_1) + (r - w_2)q_2 - r(y_1(q_1) + q_2 - D)]^+ - \gamma \left( \min\{K - \xi, D\} - q_1 \right) - \beta \left( (D - y_1(q_1))^+ - q_2 \right).
\]

(EC.7)

For any \( \hat{q}_2 \leq D \) and \( D - \hat{q}_2 < \hat{q}_1 \leq D \) (for which \( \hat{q}_1 + \hat{q}_2 - D > 0 \)) we have \( \partial \eta(\hat{q}_1, \hat{q}_2)/\partial q_1 = G(K - \hat{q}_1)(-w_1 + \gamma - \beta) \). \( G(K - \hat{q}_1) > 0 \) for \( D - \hat{q}_2 < \hat{q}_1 \leq D \) because \( D - \hat{q}_2 \geq 0, K > D \) and \( G(\cdot) > 0 \) in the support \([0, K]\). Therefore, \( \partial \eta(\hat{q}_1, \hat{q}_2)/\partial q_1 < 0 \) if and only if \( -w_1 + \gamma - \beta < 0 \). We consider three cases separately.

Case 1 \((-w_1 + \gamma - \beta > 0\)): \( \eta(\hat{q}_1, \hat{q}_2) \) is strictly increasing in the region \( D - \hat{q}_2 < \hat{q}_1 \leq D \) according to the analysis above and is continuous with respect to \( \hat{q}_1 \) (due to the continuity of \( G(\cdot) \)), therefore \( \eta(\hat{q}_1, \hat{q}_2) \) is optimized at \( \hat{q}_1 = D \) regardless of \( \hat{q}_2 \). It remains to find the optimal \( q_2 \). The buyer’s optimization problem can be rewritten as \( \max_{q_1, q_2 \leq D} \eta(q_1, q_2) \) with \( \eta(q_1, q_2) \) in (EC.7) simplified to

\[
\eta(q_1, q_2) = E[(r - w_1)\min\{K - \xi, D\} + (r - w_2)q_2 - r(\min\{K - \xi, D\} + q_2 - D)]^+ - \beta \left( (D - \min\{K - \xi, D\}) - q_2 \right).
\]

(EC.8)
The first-order condition for \( q_2 \) is \( G(q_1^* - D + K) = (r - w_2 + \beta)/(r + 2\beta) \) (and is sufficient since the buyer’s objective is strictly concave). Therefore, \( q_{2a}^* = \max \{ G^{-1}((r - w_2 + \beta)/(r + 2\beta)) + D - K, 0 \} \) and \( q_1^* = D \).

**Case 2** \((-w_1 + \gamma - \beta < 0)\): In this case, \( \partial \eta(\hat{q}_1, \hat{q}_2|\gamma, \beta)/\partial q_1 < 0 \) for any \( \hat{q}_2 \leq D \) and \( D - \hat{q}_2 < \hat{q}_1 \leq D \). Since \( \eta(q_1, q_2|\gamma, \beta) \) is continuous (due to the continuity of \( G(\cdot) \)), \( \eta(D - \hat{q}_2, \hat{q}_2|\gamma, \beta) > \eta(\hat{q}_1, \hat{q}_2|\gamma, \beta) \) and hence it must be that \( q_{1a}^* + q_{2a}^* - D = 0 \). In the rest of the analysis, we can restrict our attention to \((q_1, q_2)\) such that \( q_1 + q_2 - D = 0 \) and \( 0 \leq q_2 \leq D \). Substituting \( D - q_1 \) for \( q_2 \), the buyer’s problem can be rewritten as

\[
\max_{0 \leq q_1 \leq D} \eta(q_1, D - q_1) = \max_{0 \leq q_1 \leq D} E[(r - w_1) \min\{q_1, K - \xi\} + (r - w_2)(D - q_1) - \gamma(\min\{K - \xi, D\} - q_1) + \beta(q_1 - y_1(q_1))].
\]

The first-order condition for \( q_1 \) is \( G(K - q_{1a}^*) = (r - w_2 + \beta)/(r - w_1 + \gamma + \beta) \) (and is sufficient because the buyer’s objective is strictly concave). Consequently, \( q_{1a}^* = \min\{K - G^{-1}((r - w_2 + \beta)/(r - w_1 + \gamma + \beta)), D\} \), \( q_{2a}^* = D - q_{1a}^* \).

**Case 3** \((-w_1 + \gamma - \beta = 0)\): \( \partial \eta(\hat{q}_1, \hat{q}_2|\gamma, \beta)/\partial q_1 = 0 \) for any \( \hat{q}_2 \leq D \) and \( D - \hat{q}_2 < \hat{q}_1 \leq D \). Since \( \eta(\hat{q}_1, \hat{q}_2|\gamma, \beta) \) is continuous with respect to \( \hat{q}_1 \) and \( \hat{q}_2 \) (due to the continuity of \( G(\cdot) \)), any \( D - \hat{q}_2 \leq \hat{q}_1 \leq D \) yields the same utility given \( \hat{q}_2 \). Optimizing the buyer’s objective function with respect to \( \hat{q}_2 \) in the region where \( D - \hat{q}_2 \leq \hat{q}_1 \leq D \) yields an identical solution \( q_{2a}^* \) to Case 1. As a result, \( q_{2a}^* = \max\{G^{-1}((r - w_2 + \beta)/(r + 2\beta)) + D - K, 0\} \) and \( q_{1a}^* \in [D - q_{2a}^*, D] \).

**Proof of Corollary 1**: (a) First, we consider the case \( w_1 \leq \gamma - \beta \). By Propositions 1 and 6, utility-maximizing order quantity from S1 is strictly greater and from S2 is strictly less than standard theory predictions if and only if \( \max\{G^{-1}((r - w_2 + \beta)/(r + 2\beta)) + D - K, 0\} < D - K + G^{-1}((r - w_2)/(r - w_1)) \), or equivalently, \( (r - w_2 + \beta)/(r + 2\beta) < (r - w_2)/(r - w_1) \). This can be rewritten as \( (r - 2w_2 + w_1)/(w_1 - w_2) > -1/\beta \). Next, we consider \( w_1 > \gamma - \beta \). By Propositions 1 and 6, utility-maximizing order quantity from S1 is strictly greater and from S2 is strictly less than standard theory predictions if and only if \( \min\{K - G^{-1}((r - w_2 + \beta)/(r - w_1 + \gamma + \beta)), D\} > K - G^{-1}((r - w_2)/(r - w_1)) \), or equivalently, \( (r - w_2 + \beta)/(r - w_1 + \gamma + \beta) < (r - w_2)/(r - w_1) \). This can be rewritten as \( (r - w_2)/(r - w_1) > \beta/(\gamma + \beta) \).

If \( w_1 > \gamma - \beta \), by Propositions 1 and 6, utility-maximizing order quantity from S1 is strictly less and from S2 is strictly greater than standard theory predictions if and only if \( \min\{K - G^{-1}((r - w_2 + \beta)/(r - w_1 + \gamma + \beta)), D\} < K - G^{-1}((r - w_2)/(r - w_1)) \), or equivalently, \( (r - w_2 + \beta)/(r - w_1 + \gamma + \beta) > (r - w_2)/(r - w_1) \). This can be rewritten as \( (r - w_2)/(r - w_1) < \beta/(\gamma + \beta) \).

(b) If \( w_1 < \gamma - \beta \), the condition \( G^{-1}((r - w_2 + \beta)/(r + 2\beta)) + D - K > 0 \) ensures that the utility-maximizing order quantity from S2 is strictly greater than 0 according to Proposition 6. Then, the result follows from the fact that \( q_{1a}^* = D \) in this region.
EC.2. Decision Support Tool and Instructions for the Experiments

(a) Supplier and Effort Selection

(b) Ordering

Figure EC.1 Decision Support Tool in the SSI with Early Commitment Treatment