

Experimental Evidence of Pooling Outcomes Under Information Asymmetry

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Abstract

Operational decisions under information asymmetry can signal a firm's prospects to less-informed parties, such as investors, customers, competitors, and regulators. Consequently, managers in these settings often face a tradeoff between making an optimal decision and sending a favorable signal. We provide experimental evidence on the choices made by decision makers in such settings. Equilibrium assumptions that are commonly applied to analyze these situations yield the least cost separating outcome as the unique equilibrium. In this equilibrium, the more informed party undertakes a costly signal to resolve the information asymmetry that exists. We provide evidence, however, that participants are much more likely to pursue a pooling outcome when such an outcome is available. This result is important for research and practice because pooling and separating outcomes can yield dramatically different results and have divergent implications. We find evidence that the choice to pool is influenced by changes in the underlying newsvendor model parameters in our setting. In robustness tests, we show that choosing a pooling outcome is especially pronounced among participants who report a high level of understanding of the setting and that participants who pool are rewarded by the less informed party with higher payoffs. Finally, we demonstrate through a reexamination of Lai et al. (2012) and Cachon and Lariviere (2001) how pooling outcomes can substantively extend the implications of other extant signaling game models in the operations management literature.

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1 Introduction

Operational decisions under information asymmetry can signal a firm’s prospects to less-informed parties, such as investors, customers, competitors, and regulators. Consequently, managers in these settings often face a tradeoff between making an optimal decision and sending a favorable signal.¹ These decisions and their implications are well-examined using signaling game models in the operations literature, but there is limited empirical evidence to validate the predictions of these models. We address this gap by testing the predictive power of equilibrium assumptions in signaling games with information asymmetry among the participants.

Signaling game theory has been used to study the implications of information asymmetry in a wide array of decision contexts, including consumer purchases (Debo and Veeraraghavan 2010), competitive entry (Anand and Goyal 2009), new product introductions (Lariviere and Padmanabhan 1997), franchising (Desai and Srinivasan 1995), channel stuffing (Lai et al. 2011), supply chain coordination (Cachon and Lariviere 2001, Özer and Wei 2006, İşlegen and Plambeck 2007), and capacity investments (Lai et al. 2012, Schmidt et al. 2015). In these works, researchers must decide how to address the multiple equilibria outcomes that invariably arise. Often the emphasis is on the least cost separating outcome in which the informed party over-invests in a costly signal in order to credibly reveal her private information to the less informed party.

The alternative class of equilibria is a pooling outcome, in which the informed party either over-invests or under-invests, depending on its private information. Researchers often exclude pooling outcomes from consideration either for convenience or by invoking equilibrium assumptions that, although commonly applied, have not been empirically validated. In the first instance, Cachon and Lariviere (2001), Özer and Wei (2006) and İşlegen and Plambeck (2007) acknowledge that pooling equilibria exist, but opt to focus their analyses on the least cost separating outcome as they are particularly interested in examining situations in which the more informed player can credibly reveal her type. In the second instance, Desai and Srinivasan (1995), Lariviere and Padmanabhan (1997)

¹Managers may engage in such myopic decision making for a variety of reasons, including career advancement (Narayanan 1985, Holmström 1999) or secondary equity raises (Stein 2003). Barton (2011) uses the term “quarterly capitalism” to decry a common situation in which firms are induced to make decisions based on short-term market pressures. This issue is salient to operations management because managers generally prefer manipulating operational decisions over accounting manipulations to meet performance benchmarks (Bruns and Merchant 1990, Graham et al. 2005).

and Lai et al. (2012) make equilibrium assumptions by employing the Intuitive Criterion refinement (described in Section 2.1) to eliminate all possible pooling equilibria such that only the least cost separating equilibrium remains. More elaborate signaling games, such as those with more than one signaling mechanism (Debo and Veeraraghavan 2010), limited signaling capacity (Lai et al. 2011), or more than two players (Anand and Goyal 2009), also employ the Intuitive Criterion refinement, although the refinement may not generate a unique equilibrium prediction in these cases. Missing from this research is a consideration of alternative equilibrium assumptions, which yield different predicted outcomes and insights when applied to these models.

To shed light on this issue, we conduct a controlled experiment to examine whether separating or pooling outcomes more accurately describe actual decision making. Our work differs from literature that tests the validity of *behavioral* assumptions in models of managerial decision making. Such studies examine the behavioral factors that may influence personal choices. For instance, several behavioral experimental studies have identified that decision makers may deviate from the expected-profit-maximizing capacity choice due to decision biases, including anchoring, demand chasing, and inventory error minimization (Schweitzer and Cachon 2000, Bolton and Katok 2008, Bostian et al. 2008, Kremer et al. 2010). We contribute to this line of investigation by testing the predictive power of *equilibrium* assumptions in models of managerial decision making. In doing so, our research identifies a novel explanation of managerial deviations from model predictions in practical settings.

Our experimental design, detailed in Section 3.1, is most closely related to the capacity investment models in Bebchuk and Stole (1993), Lai et al. (2012) and Schmidt et al. (2015). Our results strongly support that decision makers adopt pooling outcomes rather than least cost separating outcomes when (1) both pooling and separating outcomes exist and (2) commonly accepted equilibrium assumptions would otherwise predict separating outcomes.

To motivate our experiment, we expand the model in Lai et al. (2012) to include consideration of pooling alternatives. We show that when pooling exists it produces higher expected payoffs for the informed party than the least cost separating outcome. These results demonstrate the intuition behind the experimental evidence supporting pooling outcomes – namely that pooling outcomes can yield higher payoffs than separating outcomes. The results also align with our finding (described in Section 5.3) that participants who make pooling decisions earn higher payoffs than those who

decide to separate.

The equilibrium assumptions that we test are predictably related to the utility payoffs that each player faces when choosing between separating and pooling equilibrium outcomes. We demonstrate this by showing that conformance to these outcomes is sensitive to changes in the underlying newsvendor model parameters. We argue that our results are therefore generalizable to other signaling game settings that also employ utility functions. In this spirit, we highlight in Section 6 how the insights from Cachon and Lariviere (2001) can be expanded by considering pooling outcomes.

2 The Impact of Refinement Choice on Outcomes

We motivate this research by examining the implications of pooling equilibria outcomes in Lai et al. (2012). In this work, the authors examine the capacity decision of a buying firm with either high (or “Big”) or low (or “Small”) random demand and a short-term interest ($\beta \in (0, 1]$) in the valuation awarded by an external investor. The buyer is aware of its demand type, but the investor is not due to information asymmetry between them. As in many signaling games, multiple equilibria exist in this setting. The authors state that they “focus only on separating equilibria in the paper because any pooling equilibrium in our model cannot survive the Intuitive Criterion refinement...” (Lai et al. 2012, p.1937). We summarize the impact of this modeling choice. Our experimental setting then leverages this model’s set up in a controlled experiment to examine whether subjects conform to the model’s predictions.

2.1 Equilibrium Refinements

The equilibrium concept used in signaling games is referred to as Perfect Bayesian Equilibrium (PBE). In a PBE, neither player has an incentive to deviate from their choices, and strategies off of the equilibrium path must be sequentially rational. For a technical definition of a PBE, refer to Fudenberg and Tirole (1991). In cases where multiple PBE exist, as reflected in the experimental scenarios that we will consider, researchers employ equilibrium assumptions in the form of refinements to the players’ out-of-equilibrium (OOE) beliefs to further pare the number of predicted PBE outcomes.

We test the validity of two equilibrium assumptions. The first is the Intuitive Criterion refinement, which is based on equilibrium dominance logic. This refinement is implied by a number of other stronger refinements, including Divinity, Universal Divinity, and Strategic Stability (Brandts and Holt 1992, Banks et al. 1994) as well as Criterion D1 and D2 (Cho and Kreps 1987). The Intuitive Criterion refinement predictions in our experiment are also predicted by this larger set of refinements, making our results more broadly generalizable. We focus our discussion explicitly on the Intuitive Criterion refinement because it is the most commonly applied refinement approach in the literature and arguably the most familiar to operations management researchers. For instance, Riley (2001) notes that the “Intuitive Criterion has dominated the literature in the years since its introduction.”

The second refinement mechanism we test is the Undeclared refinement, which is based on Pareto optimization logic. While not as widely employed in the literature², we argue that it may be more appropriate to describe decision outcomes in operations management settings because it predicts outcomes that result in a Pareto improvement in the firm’s payoff regardless of the firm’s type.

The question of which equilibrium refinement assumption is most predictive remains unsettled. Banks et al. (1994) test which refinement participants employ from a set of nested refinements that use increasingly stringent assumptions related to equilibrium dominance. They explicitly test and find support for the application of the Intuitive Criterion refinement, but do not consider refinements based on Pareto optimization such as the Undeclared refinement. Similarly, Brandts and Holt (1992, 1993) also consider the predictive power of equilibrium dominance refinements, including the Intuitive Criterion, but not Pareto dominance refinements. Other research explores how adaptive learning over repeat play may influence which equilibrium participants converge upon (Brandts and Holt 1996, Cooper et al. 1997). While finding support for the Intuitive Criterion, they also find that the Intuitive Criterion does not explain all sustained equilibrium behavior. We add to this stream of research by comparing the predictive power of equilibrium assumptions based on equilibrium dominance and Pareto optimization logic, which has not been the subject of previous experimental testing.

²Google Scholar reports that by the mid-2015 there were 289 citations to Mailath et al. (1993) (which introduced the Undeclared refinement) compared to 2,985 citations to Cho and Kreps (1987) (which introduced the Intuitive Criterion refinement).

2.1.1 The Intuitive Criterion Refinement

In our context, the Intuitive Criterion refinement is applied by considering all possible OOE capacity levels for a particular PBE and identifying whether, compared to the PBE results, a capacity choice exists that *would not* provide a “Small” demand firm with a higher payoff using the highest valuation the investor could assign but *would* provide a “Big” demand firm with a higher payoff using the highest valuation the investor could assign. If such a capacity choice does exist then the Intuitive Criterion refinement eliminates the focal PBE. In signaling games involving two players, one costly signal with continuous and infinite support, two types of the informed player, and conformance with the single crossing property, the Intuitive Criterion eliminates all but the least cost separating PBE. For the formal definition of the Intuitive Criterion refinement, please refer to Cho and Kreps (1987).

Although it is widely applied in the literature, there are practical concerns with the Intuitive Criterion that may make it inappropriate in some operations management settings. For instance, the Intuitive Criterion refinement (1) asserts that decision makers will make choices that involve costly signaling even if such choices are Pareto-dominated by alternative choices (Mailath et al. 1993), (2) assumes that counterfactual information can be communicated in the game without being explicitly modeled (Salanie 2005), (3) may eliminate all choices from consideration when signals have discrete support (Schmidt et al. 2015), and (4) can lead to implausible outcomes (Bolton and Dewatripont 2005).

2.1.2 The Undefeated Refinement

The Undefeated refinement is based on Pareto-optimization logic. If there exists multiple PBE in a game, and one of those PBE provides a Pareto improvement in payoffs for all types of the informed player compared to one of the alternative PBE, then the Pareto dominated PBE is eliminated. A PBE which is not Pareto dominated by any alternative PBE is said to be “undefeated” or to survive the Undefeated refinement. As a result, the Undefeated refinement predicts the outcome which yields the highest equilibrium payoff for each type of informed player. In some cases this may be a separating PBE and in other cases this may be a pooling PBE. For a technical definition of the Undefeated refinement, please refer to Mailath et al. (1993). In some cases there may exist multiple pooling PBE that survive the Undefeated refinement. For ease of exposition in our analysis

of Lai et al. (2012) and Cachon and Lariviere (2001), we focus on the unique pooling PBE that is a lexicographically maximum sequential equilibrium (LMSE). According to Mailath et al. (1993), a PBE is a LMSE if among all PBE it maximizes the utility for a high type, and conditional on maximizing the utility for a high type, it then maximizes the utility for a low type. Using a LMSE to identify a unique PBE is intuitively appealing because typically a low type wishes to be perceived as a high type rather than the opposite.

Although not widely adopted, the Undeclared refinement has been applied in the finance and economics literature (Spiegel and Spulber 1997, Taylor 1999, Gomes 2000, Fishman and Hagerty 2003) and it addresses the concerns highlighted in Section 2.1.1 about the Intuitive Criterion refinement. An intuitive result of the Undeclared refinement is that when one or more pooling PBE exist, then one pooling PBE which will survive the Undeclared refinement is an outcome in which every type of the informed player mimics the optimal pooling choice of the highest type.³

2.2 An Example of the Impact of Refinement Choice

We replicate the example from Section 4 of Lai et al. (2012) using the Intuitive Criterion refinement and compare the results to those obtained if the Undeclared refinement is used instead. In this example, the buying firm faces a newsvendor profit function with a selling price (p) of 20, a wholesale price (w) of 8, and a buyback price (b) of 4. The supplier has a production cost (c) of 5. The prior probability that the buyer's demand signal is high (λ) is 0.5 and demand follows a gamma distribution with a scale parameter of 5 for both buyer types, a shape parameter of 1.5 for buyer types facing a high demand, and a shape parameter of 1.0 for buyer types facing a low demand. The buyer chooses a stocking level q , which may signal its type to the uninformed party. Refer to Lai et al. (2012) for further details.

There are a range of model parameters over which a separating equilibrium exists and a sub-

³This can be valid even as the game structure gets complex. For instance, under infinite types, infinite strategies, and infinite state spaces, a more rigorous application for a given state space is the following program: (1) the highest firm type identifies her optimal capacity choice provided the investors' beliefs are unchanged (i.e. posterior beliefs = prior beliefs), (2) the highest type compares her utility at that capacity level with her utility from separating, and (3) if the highest type receives a higher utility under the capacity level from (1), then all firm types should choose the capacity level from (1) provided it generates a higher utility for them compared to separating. Step (1) can be done easily by, for instance, solving a newsvendor model in the case of stochastic demand. Steps (2) and (3) can be done by solving the utility function for each firm type at the two alternative capacity choices.

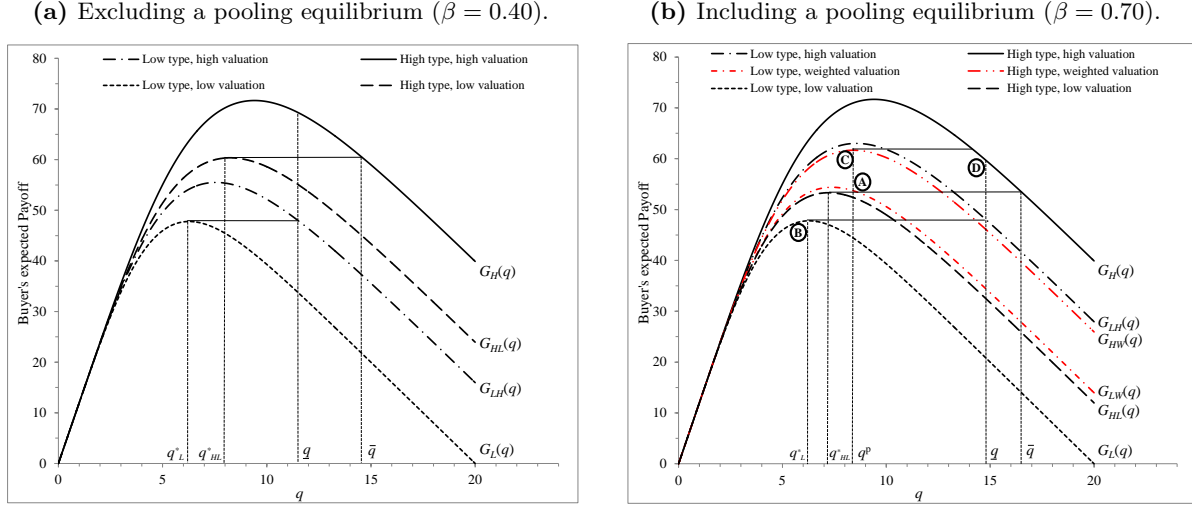
stantial subset of this range over which both separating and pooling equilibria exist. Figure 1a, corresponding to Figure 2 in Lai et al. (2012), utilizes the setup described above and $\beta = 0.4$ to exemplify an instance in which only a separating equilibrium exists. In the separating equilibrium the low type chooses q_L^* and the high type chooses \underline{q} . Figure 1b, utilizes the same setup and $\beta = 0.7$ to exemplify an instance in which both a pooling and a separating equilibrium exist. In the pooling equilibrium, both buyer types choose capacity q^p while in the separating equilibrium the low type chooses q_L^* and the high type chooses \underline{q} (note that \underline{q} in Figure 1b is larger than in Figure 1a, reflecting the higher cost of separating as β increases). Figure 1b makes clear the benefit accrued to the buyer by pooling. In the pooling outcome, the high type buyer receives a utility of 61.7 (labeled point C), which is 4% higher than the utility of 59.5 from the separating outcome (point D). The low type buyer receives a utility of 53.7 in the pooling outcome (point A), which is 12% higher than the utility of 47.8 from the separating outcome (point B).

The intuition for why an increase in short term-ism leads to a pooling equilibrium under the Undefeated refinement is clear in Figures 1b and 1a. Such an increase gives the low type buyer a greater incentive to secure a higher short-term valuation by mimicking the high type buyer's stocking level. This increases the cost of separating for the high type, which in turn makes a pooling outcome more attractive relative to separating for the high type. Schmidt et al. (2015) show rigorously that other model parameters, including a decrease in the prior belief that the firm is a low type and changes in the newsvendor model parameters, can increase the likelihood that a pooling equilibrium exists.

Expanding on this example, Lai et al. (2012) show that buyers must send a costly signal in order to separate when $\beta > \hat{\beta}$, where $\hat{\beta} \approx 0.21$. It can be shown that a pooling equilibrium also exists when $\beta > \tilde{\beta}$, where $\tilde{\beta} \approx 0.60$.⁴ As shown in Figure 2a, the pooling equilibrium provides a materially higher expected utility for the buyer compared to the separating equilibrium. In fact, the pooling equilibrium becomes an increasingly attractive alternative to the separating equilibrium as β increases and the cost of separating drags down the buyer's expected utility under the separating equilibrium. The discontinuity in Figure 2a at $\beta = 0.60$ can be understood by examining Figure 2b. This figure shows the percent improvement of the pooling equilibrium compared to the separating equilibrium for each buyer type and in expectation. At the threshold value of $\beta = 0.60$, the high

⁴Different model parameters will result in different threshold values for $\hat{\beta}$ and $\tilde{\beta}$.

Figure 1: Buyer's Profit as a Function of Capacity.



type buyer is ambivalent between pooling and separating, while the low type buyer strictly prefers to pool. Above this threshold, both types benefit from pooling, leading to the existence of a pooling equilibrium.

Note that the objective of our analysis is to identify participant choices when both separating and pooling equilibria exist ($\beta > \tilde{\beta}$ in this example). When only the separating equilibria exists ($\beta < \tilde{\beta}$) the equilibrium assumptions tested in our experiment yield identical predictions.

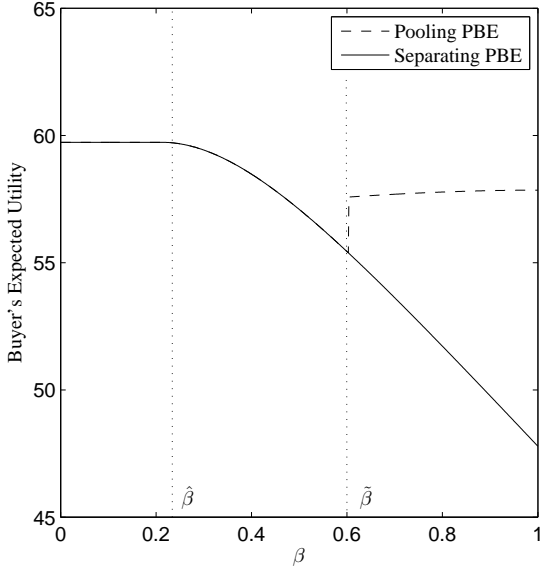
3 Model and Scenario Development

3.1 Player Payoffs

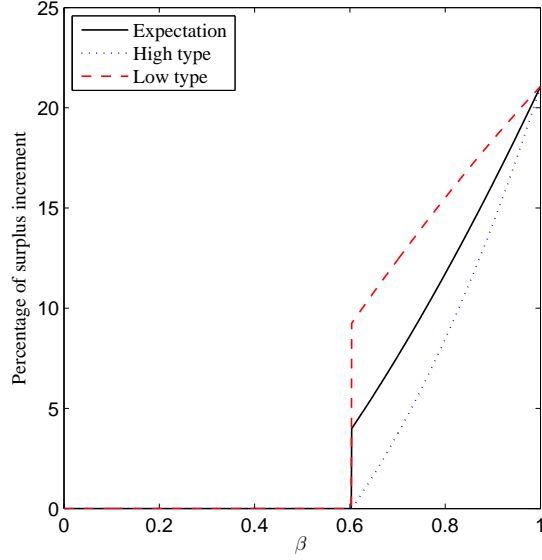
The payoffs in our experiment are theoretically grounded by models employed in Bebchuk and Stole (1993), Lai et al. (2012) and Schmidt et al. (2015). We apply the following set up in Section 3.2 to develop scenarios for the experiment. There are two players, the firm (denoted F) and an investor in the firm (denoted I). The firm can be one of two types with respect to its market prospects – a “Small” opportunity type (τ_S) or a “Big” opportunity type (τ_B). The probability that a firm will be type τ_S is denoted $(1 - \lambda)$ and type τ_B is denoted λ , where $\lambda \in (0, 1)$. The firm types differ only in the probability distribution of demand. The demand distribution for a τ_B type first order stochastically dominates (FOSD) the demand distribution for a τ_S type, i.e., $F_S(x) \geq F_B(x)$ for

Figure 2: Buyer's Expected Utility and Surplus Benefit from a Pooling Equilibrium

(a) Buyer's Expected Utility Under Pooling and Separating Equilibria



(b) Percent Improvement for Each Buyer Type from a Pooling Equilibrium Compared to a Separating Equilibrium



all $x \in \mathbb{R}^+$ and $F_S(x) > F_B(x)$ for some x , where $F_\tau(\cdot)$ is the cumulative distribution function of demand for type τ . The assumptions reflected in our experiment⁵ are commonly used in the signaling game literature (Kreps and Sobel 1992).

The firm must decide how many stores to open (q), where q can be in multiples of a capacity increment Q , i.e., $q = nQ$ for some integer n .⁶ The firm's payoff is a linear combination of the investor's valuation of the firm ($\rho(q)$) and the firm's expected profit ($\pi(\tau, q)$), weighted by β and $1 - \beta$ respectively, where $\beta \in (0, 1]$:

$$U(\tau, q, \rho) = \beta \rho(q) + (1 - \beta) \pi(\tau, q). \quad (1)$$

A larger value of β corresponds to a higher emphasis on short-term valuation and a correspondingly lower emphasis on the expected long-term expected profits. The firm's expected profit is derived

⁵Two players, one costly signal, two types of the informed player, and the single crossing property holds.

⁶Using discrete choices simplifies the experience for the subject and is consistent with findings in the experimental literature that limiting the choice set is a valid de-biasing strategy (Bolton and Katok 2008).

by solving the newsvendor model, $\pi(\tau, q) = E_\tau [p \min\{q, x\} + w(q - x)^+ - bq]$ where p is the selling price, w is the wholesale cost, and b is the buyback price of unsold inventory; $p > w > b$. Note that if $\beta = 0$ then Equation 1 resolves to the classical newsvendor model.

Upon seeing the number of stores q that the firm decides to open, the investor must decide what valuation $\rho(q)$ to assign to the firm. The investor can assign three values to the firm – “Big” (which corresponds to $\rho(q) = \pi(\tau_B, q)$), “Weighted” (which corresponds to $\rho(q) = (1 - \lambda)\pi(\tau_S, q) + \lambda\pi(\tau_B, q)$), or “Small” (which corresponds to $\rho(q) = \pi(\tau_S, q)$). The investor’s payoff depends on being as close as possible to the true value of the firm:

$$V(\tau, q, \rho) = -[\pi(\tau, q) - \rho(q)]^2.$$

3.2 Scenario Development

Following the model described in Section 3.1, we developed a set of 4,752 scenarios for potential inclusion in the experiment. These scenarios were generated using a manageable subset of the parameters utilized in Schmidt et al. (2015). Specifically, the firm faces a log-normal demand distribution regardless of its type with a log-scale parameter for a τ_S type of $\mu_S = 6.0$ and for a τ_B type of $\mu_B \in \{6.25, 6.50\}$. The shape parameter takes values $\sigma^2 \in \{0.15, 0.25\}$. The unit price (p) ranges from 0.75 to 1.00 in increments of 0.05, unit buyback price / salvage value (b) ranges from 0.0 to 0.10 in increments of 0.05, and unit wholesale price is $w = 0.4$. Short-termism (β) ranges from 0.10 to 0.60 in increments of 0.05, the equity holder’s prior beliefs that the firm is type τ_S ($1 - \lambda$) ranges from 0.30 to 0.40 in increments of 0.05, and the capacity investment is discrete with $Q \in \{100, 200\}$.

We then identified three scenarios from this set of 4,752 scenarios, and manually confirmed that each selected scenario satisfies two conditions. First, the scenario must simultaneously test the predictive power of the Undeclared and Intuitive Criterion refinements. To achieve this, we used scenarios with four sequential capacity values based on the capacity increment Q . The first capacity value must optimize the payoff for a τ_S type when receiving a *low* valuation, survive the Intuitive Criterion refinement, and be eliminated by the Undeclared refinement. The second capacity value must optimize the payoff for a τ_B type when receiving a *weighted* valuation, survive the Undeclared refinement, and be eliminated by the Intuitive Criterion refinement. The third capacity value must not be a PBE (it is necessary for inclusion due to its role in the application of the Intuitive Criterion

refinement). The fourth capacity value must be the least-cost separating capacity for a τ_B type, survive the Intuitive Criterion refinement, and be eliminated by the Undefeated refinement.

The second condition for a scenario’s inclusion is that if the unit price used in the scenario is incremented by 0.05 it yields a new scenario with four valid capacity values. This condition allowed us to test the impact on participant choices of changing the unit price in the newsvendor model. If a scenario did not meet both conditions, another scenario from the pool of 4,752 scenarios was selected and manually evaluated. This process was repeated until three scenarios meeting both conditions were identified. By incrementing the price by 0.05 in each of these three scenarios, three additional scenarios were generated, for a total of six scenarios in the experiment. Table 1 summarizes the model parameters used to generate each of the six scenarios included in the experiment.

To more realistically reflect the store opening choice that is the basis of the firm’s decision in the experiment, we divided the capacity options by 100 in the scenarios. We applied a positive linear transformation to the payoffs in each scenario so that the range of possible payments fit our budget limitations. Positive linear transformations are commonly used to represent the same preferences as the original payoff function while preserving the expected utility property (Mas-Colell et al. 1995).

None of the choices in any scenario are strictly dominated, so there is no guarantee that any particular choice will result in a player realizing a higher payoff. A choice is strictly dominated for a firm type if the best utility that firm type could possibly achieve by sending that signal is strictly lower than the worst utility that firm type could possibly achieve by sending some other signal. For a technical definition of Strict Dominance, refer to (Mas-Colell et al. 1995, p.469).

Figure 3a provides the extensive form view of scenario 1, shown from the firm’s perspective. The investor’s perspective was identical to that of the firm, except for minor coloration and prompt differences, which served to highlight each player’s choice set and payoffs. In this scenario the firm faced a “Big” opportunity with an ex-ante probability of 65%. A “Big” opportunity firm could choose to open 5, 6 or 7 stores, while a “Small” opportunity firm could choose to open 4, 5, or 6 stores. If the firm chose to open a pooling quantity of either 5 or 6 stores, then the investor was prompted to decide whether to award the firm a “Small,” “Weighted,” or “Big” valuation. If instead, the firm chose a separating quantity of 4 or 7 stores, the investor was notified of the quantity and informed that the firm is a “Small” or “Big” opportunity firm, respectively. The

players' payoffs for each outcome are summarized near the terminal node for the outcome.

Figure 3: Extensive form of Scenarios 1 and 2.

(a) Extensive form of Scenario 1, shown from the firm's perspective. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a "Small" opportunity type firm.

(b) Extensive form of Scenario 2, shown from the investor's perspective. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a "Small" opportunity type firm.



There are two PBE in Scenario 1, (1) the least cost separating PBE in which a "Big" type chooses 7 stores and a "Small" type chooses 4 stores and (2) a pooling PBE in which both firm types choose 5 stores. In the separating PBE, the "Big" type is guaranteed to earn \$0.67 and the "Small" type is guaranteed to earn \$0.52. The investor earns \$1.00 regardless of the firm's type. In the pooling PBE at 5 stores, the "Big" type earns \$0.84 under a "Weighted" valuation and the "Small" type earns \$0.63 under a "Weighted" valuation. The investor earns \$0.90 in expectation by awarding a "Weighted" valuation ($0.65 \times \$0.95 + 0.35 \times \0.82). Opening 6 stores is not a PBE. It is not a separating PBE since a "Big" type cannot separate from a "Small" type by opening 6 stores, nor is it a pooling PBE since the "Small" type receives a higher payoff by opening 4 stores than she does by opening 6 stores and receiving a "Weighted" valuation.

The separating PBE in each scenario survives the Intuitive Criterion refinement. The pooling PBE at 5 stores does not survive the Intuitive Criterion refinement because there exists an alternative choice (opening 6 stores), which (1) provides the "Small" opportunity firm with a lower payoff under a "Big" valuation compared to the payoff she receives under a "Weighted" valuation when

opening 5 stores and (2) provides the “Big” opportunity firm with a higher payoff under a “Big” valuation compared to the payoff she receives under a “Weighted” valuation when opening 5 stores. In other words, the best payoff that a “Small” firm can get by opening 6 stores (\$0.59) is less than the payoff they receive under a “Weighted” valuation when opening 5 stores (\$0.63), and the best payoff that a “Big” firm can get by opening 6 stores (\$0.89) is greater than the payoff they receive under a “Weighted” valuation when opening 5 stores (\$0.84).

The separating PBE does not survive the Undefeated refinement since there exists an alternative PBE (pooling on 5 stores) which provides a higher equilibrium payoff for both firm types. Specifically, the “Small” type receives a payoff of \$0.63 under a “Weighted” valuation when opening 5 stores compared to a payoff of \$0.52 by opening 4 stores in the separating PBE. The “Big” type receives a payoff of \$0.84 under a “Weighted” valuation when opening 5 stores compared to a payoff of \$0.67 by opening 7 stores in the separating PBE. The pooling PBE at 5 stores survives the Undefeated refinement since there does not exist an alternative PBE which provides a higher equilibrium payoff for both firm types.

Figure 3b provides the extensive form view of Scenario 2 from the investor’s perspective. Note that the structure of this scenario is similar to that of Scenario 1, although with different payoffs. In this case, the payoffs are determined by increasing the unit price by 6.67% (from 0.75 to 0.80) in the underlying newsvendor model used to generate the player payoffs. Figures 5 and 6 in the Appendix provide the extensive forms for the remaining 4 scenarios. Scenario 4 is similar to Scenario 3 except that the unit price is increased by 6.67% (from 0.75 to 0.80) in the underlying newsvendor model. Scenario 6 is similar to Scenario 5 except that the unit price is increased by 5.88% (from 0.85 to 0.90) in the underlying newsvendor model. This design facilitates our analysis by enabling us to examine whether participants acted consistently across scenario pairs, as well as whether participants’ choices were sensitive to changes in the underlying Newsvendor parameters. Table 2 identifies the outcomes predicted by the Undefeated and Intuitive Criterion refinements in each experimental scenario.

4 Experiment

Participants. Participants (N=228, median age=25, 48% female) completed this experiment in a laboratory at a university on the American East Coast in exchange for \$15.00 plus an average bonus

of \$10.37, which was based on the outcomes of the experimental games in which they participated. The participants belonged to a subject pool associated with the university’s business school, and registered for the study in response to an online posting. Roughly two-thirds of the participants were full-time undergraduate or graduate students hailing from a wide array of fields. The remaining participants were residents who lived in the surrounding community. Table 3 summarizes the participant demographic information.

Experimental design and procedure. At the beginning of the session, a monitor read a script aloud to familiarize the participants with their roles and the experimental procedure. The text of the script is provided in the Online Appendix, and the accompanying presentation slides are available from the authors upon request. Throughout the session, participants engaged with one another anonymously, through a web-based software application that was developed for this experiment. The software restricted communication between participants explicitly to the decisions described below. Participants were not permitted to engage with one another outside of the software.

Participants considered each of the six scenarios from the perspectives of both a firm and an investor, resulting in a total of 12 rounds. At the beginning of each round, participants were randomly and anonymously paired with one another and notified of their role for the round (firm or investor). Next, the matched pair of participants was presented with the extensive form view of a randomly selected scenario and the probability the firm faced a “Big” opportunity. Upon seeing the extensive form representation, participants were asked to anticipate the choices they would make under different realizations of the scenario. Participants playing the role of the firm were asked how many stores they would open if they faced a “Big” or “Small” opportunity. The quantity choices available to the firm represented different combinations of separating PBE, pooling PBE, and choices that were not PBE. Concurrently, participants playing the role of the investor were asked whether they would award a “Big,” “Weighted,” or “Small” valuation to the firm, if they observed the firm select each of the pooling quantities under its consideration.

We elicited strategies from participants prior to capturing their direct responses during actual game play for two reasons. First, by asking the participants to predefine their strategies, we hoped to encourage them to consider each scenario from different perspectives before committing to a final decision. Second, by engaging in this staged approach, we were able to control for whether

firms and investors deviated from their original strategies once information had been revealed to them.⁷

Next, based on the stated probability, the software randomly designated the firm to be facing a “Big” or “Small” opportunity, revealing this information only to the participant playing the role of the firm. Upon receiving this private information, the participant playing the role of the firm could confirm or revise the number of stores she chose to open. Then, the number of stores opened by the firm (but not its type) was revealed to the investor, who could in turn, confirm or revise her valuation.

At the end of each round, the payoff received by the firm depended on the firm’s type and store quantity, as well as the valuation chosen by the investor. The payoff for the investor depended on their choice being as close as possible to the firm’s actual type. To remove the potential confound of order effects, we counterbalanced the presentation order of the scenarios. However, we also wished to facilitate a deep understanding of the game among the participants. To that end, participants completed a scenario in one role (firm or investor) and then completed the same scenario in the other role before moving on to a new scenario. Finally, we sought to mitigate the effects of retaliation from past rounds by pairing participants with new, anonymous, and randomly-selected partners at the beginning of each round.

5 Results

5.1 Predictive Power of Intuitive Criterion and Undefeated Refinements

Table 4 presents the degree to which participants’ decisions conformed with the predictions of the Undefeated and Intuitive Criterion refinements in each experimental scenario. In our experiment, the majority of participants’ decisions followed the predictions of the Undefeated refinement. Its predictive power across scenarios ranged from a low of 55.7% accuracy for Scenario 4 to a high of

⁷A strength of the strategy method is that it may lead participants to make more thoughtful decisions by encouraging them to think through multiple possibilities (Brandts and Charness 2011), but critics argue that having to submit entire strategies forces participants to think about each information set in a different way than if they could primarily concentrate on those information sets that arise in the course of the game (Roth 1995). Hence, we leverage the strategy method to help participants fully consider each scenario, but we perform our analyses on direct response data captured during actual game play.

71.1% accuracy for both Scenarios 1 and 5. Participants' decisions matched the predictions of the Intuitive Criterion on far fewer occasions. Its predictive power across scenarios ranged from a low of 17.1% accuracy for Scenarios 1 and 3 to a high of 29.4% accuracy for Scenario 2. Subjects made choices that conformed with neither refinement between 10.7% of the time (Scenario 2) and 19.7% of the time (Scenario 3).

We test whether the predictive power of each refinement is statistically significant using two-sided binomial tests of the null hypothesis that each refinement has no predictive power. If the conformance of participants' decisions to the predictions of each refinement were the product of random chance, then we would expect to see decisions conform to the refinement predictions one third of the time since each scenario has three choices. The tests evaluate the degree to which choices deviate from these expectations. We evaluate the predictive power of each refinement in each scenario individually and then in aggregate. Participants' decisions conformed with the predictions of the Undefeated refinement in all six scenarios ($p < 0.001$ two-sided for each scenario). Aggregating across all scenarios, we found support for the predictive power of the Undefeated refinement, which predicted 63.5% of participants' decisions ($p < 0.001$; two-sided), relative to an expectation of 33.3% if it instead had no predictive power.⁸

In contrast, participants' decisions were not predicted by the Intuitive Criterion refinement. In five of the six scenarios, participants made choices which conformed with the Intuitive Criterion refinement *less often* than what would be expected if participants were simply making random selections ($p < 0.05$ two-sided, for Scenario 4, and $p < 0.001$ two-sided for Scenarios 1, 3, 5 and 6). The sole exception is Scenario 2 in which 29.4% ($p = 0.23$; two-sided) of participant responses conformed with the Intuitive Criterion refinement, which is statistically indistinguishable from an expectation of 33.3%. Across all scenarios combined, we find support that the Intuitive Criterion refinement, which predicted 20.9% of participants' decisions ($p < 0.001$ two-sided), has less predictive power than an expectation of 33.3% if participant choices were purely random.⁹

⁸As a robustness test, we also considered just the first scenario seen by each participant. Since scenarios are randomly assigned, different scenarios will be presented first to different participants. We find strong support for the predictive power of the Undefeated refinement, which predicted 56.1% of participants' decisions, relative to an expectation of 33.3% ($p < 0.001$; two-sided).

⁹We again considered just the first scenario seen by each participant and find that firms made choices which conformed with the Intuitive Criterion refinement 24.6% of the time, far less often than what would be expected if participants were simply making random selections ($p < 0.01$ two-sided).

To test which refinement is more predictive, we perform a two-sided binomial test of the null hypothesis that there is no difference in the predictive power of the two refinements. We discard 212 out of 1,368 observations in which participants made decisions that were not predicted by either refinement, leaving 1,156 observations.¹⁰ If neither refinement were predictive, then we would expect to see participants splitting their decisions evenly between the options. However, 869 of 1,156 choices (75.2%) conformed with the Undeclared refinement, while the remaining 287 choices (24.8%) conformed with the Intuitive Criterion refinement. Results of the binomial tests reject the null hypothesis in favor of the alternative that the Undeclared refinement is more predictive than the Intuitive Criterion refinement ($p < 0.001$; two-sided).

5.2 Sensitivity to Newsvendor Unit Price

As described in Section 3.2, Scenarios 1 and 2 are the same in all respects except the unit price used to determine the players' payoffs is 6.67% higher in Scenario 2. The unit price has also been increased in Scenario 4 relative to Scenario 3 and in Scenario 6 relative to Scenario 5. We use two-sided binomial tests to determine whether participant choices differ across these scenario pairs. Rows 2 and 4 of Table 4 summarize these results.

As shown in Table 4, conformance with the Undeclared refinement is higher in Scenarios 1, 3, and 5 than in Scenarios 2, 4 and 6. The difference in the proportion of participants whose choice conforms with the Undeclared refinement between Scenarios 1 and 2 (diff = 0.114, $p < 0.05$ two-sided), Scenarios 3 and 4 (diff = 0.075, $p = 0.11$ two-sided), and Scenarios 5 and 6 (diff = 0.105, $p < 0.05$ two-sided), are all positive and the first and third differences are statistically significant. Comparing all odd scenarios to all even scenarios, the difference is positive and statistically significant (diff = 0.098, $p < 0.001$ two-sided). Conformance with the Intuitive Criterion refinement is lower in Scenarios 1, 3, and 5 than in Scenarios 2, 4 and 6. The difference in the proportion of participants whose choice conforms with the Intuitive Criterion refinement between Scenarios 1 and 2 (diff = -0.123, $p < 0.01$ two-sided), Scenarios 3 and 4 (diff = -0.088, $p < 0.05$ two-sided), and Scenarios 5 and 6 (diff = -0.048, $p = 0.18$ two-sided), are all negative and the first and second differences are statistically significant. Comparing all odd scenarios to all even scenarios, the difference

¹⁰We note that participants made choices that failed to conform with either refinement in 15.5% of cases ($p < 0.001$ two-sided), which is significantly less frequent than random chance.

is negative and statistically significant (diff = -0.086, $p < 0.001$ two-sided).

To understand these results, recall from Section 2.1 that the Undefeated refinement predicts the outcome (either a separating PBE or a pooling PBE) which provides the highest equilibrium payoff to both firm types. As the differential payoff between the PBE alternatives is reduced, participants will become indifferent between them. In our scenarios, an increase in unit price reduces the proportional improvement of the pooling PBE payoff relative to the separating PBE payoff for “Big” opportunity firms while leaving the proportional payoffs largely unchanged for the “Small” opportunity firms. For instance, in Scenario 1 the equilibrium payoff for the “Big” opportunity firm that chooses a pooling PBE at 5 stores is 25% higher than the payoff received by separating (\$0.84 versus \$0.67). The increase in unit price in Scenario 2 reduces this improvement in the equilibrium payoff to 11% (\$1.15 versus \$1.04).¹¹ The change in relative payoffs between scenarios is much less pronounced for the “Small” opportunity firms, which receive a 21% higher payoff in the pooling PBE in Scenario 1 (\$0.63 versus \$0.52) and a 19% higher payoff in Scenario 2 (\$0.92 versus \$0.77).¹²

Using this rationale, we expect to see a smaller proportion of “Big” opportunity firms comply with the Undefeated refinement in Scenario 2 compared to Scenario 1, and approximately the same proportion of “Small” opportunity firms. As summarized in Table 5, our results confirm this intuition. The proportion of “Big” opportunity firms making choices that comply with the Undefeated refinement is 19.3 percentage points lower in Scenario 2 compared to Scenario 1 ($p < 0.001$ two-sided) while the proportion of “Small” opportunity firms making choices that comply with the Undefeated refinement is 0.9 percentage points lower in Scenario 2 compared to Scenario 1 ($p = 0.90$ two-sided). Table 5 shows similar results comparing Scenario 3 to Scenario 4 and Scenario 5 to Scenario 6.

These findings support the underlying logic behind the Undefeated refinement that firms make choices based on the Pareto improvement in equilibrium outcomes. As the improvement in equilibrium payoffs between a pooling PBE and a separating PBE increases (diminishes), the pooling PBE

¹¹The pattern of a material reduction in the proportional improvement in the “Big” opportunity firm’s payoffs from the pooling PBE compared to the separating PBE is also present between Scenarios 3 (24% improvement) and 4 (12% improvement) and between Scenarios 5 (16% improvement) and 6 (6% improvement).

¹²There is also a much more muted change in the proportional improvement in the “Small” opportunity firm’s payoffs from the pooling PBE compared to the separating PBE between Scenarios 3 (10% improvement) and 4 (14% improvement) and between Scenarios 5 (24% improvement) and 6 (20% improvement).

becomes more (less) attractive to decision makers. The relationships between the model parameters and payoffs can be complex in a discrete capacity model such as ours, and these results show that the predictive power of refinements is sensitive to changes in the model parameters used to generate the payoffs. This highlights that model parameters can influence whether participants conform to different refinement theories beyond simply determining whether an equilibrium outcome exists and survives a particular refinement.¹³

5.3 Robustness Tests

We run robustness tests to evaluate (1) whether the participant’s level of understanding of the game and the complexity of the game influence the predictive power of each refinement and (2) whether choices consistent with each refinement have an impact on payoffs. Table 6 summarizes the variables used in this analysis and Table 7 provides summary statistics and correlations.

5.3.1 Impact of Understanding on Refinement Predictions

In practical settings, decision makers are apt to possess a sound understanding of the implications of their decisions. This is reflected in economic models that examine such decisions, which often assume that decision makers behave rationally in assessing the repercussions of their choices.¹⁴

Measures. To analyze whether the participant’s level of understanding of the decision setting is associated with her making choices that are predicted by either the Undeclared or Intuitive Criterion refinements, we use a dichotomous variable, *Understanding*. Each participant assessed their level of understanding by responding to a post-experiment survey, which asked “On a scale of 1-7 (1: ‘I did not understand the game at all’, 7: ‘I understood the game completely’) how well do you feel you understood the game we just played?” Based on these responses, we set *Understanding*

¹³It is interesting to note that the Undeclared refinement has significant predictive power even when the improvement in the equilibrium payout is quite small. For instance, in Scenario 6 a “Big” opportunity firm’s equilibrium payoff from the pooling PBE (\$0.93) is only 6% higher than that from the separating PBE (\$0.88), and yet 53.8% of “Big” opportunity firms comply with the Undeclared refinement prediction, significantly more ($p < 0.001$ two-sided) than the 33.3% expected from random choice.

¹⁴We implemented several features in our experimental design to foster a better understanding of the game among the participants, including asking participants to enter their strategies before each round of play, having participants switch roles and play the game both as a firm and an investor, and playing multiple rounds.

to ‘1’ if the participant rated their understanding as a ‘5’ or higher and ‘0’ if they rated it a ‘4’ or lower. We encode participants that did not respond to this question as a ‘0’, but isolate this effect using the variable *Understanding - No Response* which is set to ‘1’ if the participant did not respond and ‘0’ otherwise. Participants generally indicated a high level of understanding of the game – 86.3% of participants responded with a 5, 6 or 7 and the mean response was 5.89. As a consequence, some of the response categories are so sparsely populated that we cannot use the full 7-point scale in our analysis. We do, however, run robustness tests using more granular measures of understanding than the dichotomous measure we use to present our main results. Our findings are unchanged with these alternative measures of understanding.

We utilize two dichotomous dependent variables in this analysis. *Undefeated* and *Intuitive* capture whether participants make choices consistent with the Undefeated or Intuitive Criterion refinement. *Undefeated* is set to ‘1’ if the firm’s choice conforms to the Undefeated refinement, and ‘0’ if it does not. *Intuitive* is set to ‘1’ if the firm’s choice conforms to the Intuitive Criterion refinement, and ‘0’ if it does not.

We collect several additional variables in each round of the experiment to track information related to the set up and play of the game. *Big* is set to ‘1’ to identify those participants that are randomly assigned to have a “Big” opportunity in the current round. *Switch* identifies whether the participant’s final choice deviated from the initial strategy they entered prior to learning their type. *Session* identifies the experimental session in which the participant participated. *Sequence* reflects the order in which a scenario is presented to a participant and captures changes in outcomes as participants see more scenarios. We also include demographic information on the participants. *Age* is the age of the participant at the time of the experiment. *Female* identifies the participant’s gender. *Ethnicity* reflects the participant’s self-affiliated ethnicity. *Education* is a categorical variable capturing the most recent level of education attained by the participant. *ESL* reflects whether the participant considers English to be their second language.

Empirical Model. We are interested in the relationship between each participant’s self-reported level of understanding of the game and the likelihood that their decisions are predicted by either the Undefeated refinement or the Intuitive Criterion refinement. Any predictive power associated with the refinements could justifiably be called into question if participants report having a low understanding of the game. Indeed, we expect that in most managerial contexts, decision makers

have a high level of understanding with regard to their choices and their potential implications. As such, we are particularly interested in which refinement mechanism best predicts the choices of decision makers who report a high level of understanding. We examine this relationship for the Undefeated refinement by estimating the following logistic model, with robust standard errors clustered by participant:

$$\begin{aligned} Pr(Undefeated_{ij}) = F(\beta_0 + \beta_1 \cdot Understanding_i + \beta_2 \cdot Understanding - No Response_i + \\ \beta_3 \cdot Big_{ij} + \beta_4 \cdot Switch_{ij} + \xi'X_i + \epsilon_{ij}), \end{aligned} \quad (2)$$

where subscript i denotes the participant and j denotes the round. The function $F(\cdot)$ refers to the logistic function. To examine this relationship for the Intuitive Criterion refinement, *Intuitive* is used as the dependent variable in place of *Undefeated*. The vector X_i includes control variables: *Session*, *Sequence*, *Age*, *Female*, *Ethnicity*, *Education*, and *ESL*. We include *Session* to account for any structural issues that are constant within a session (time of day, for instance). *Sequence* controls for the possibility that a learning effect may be driving our result. We include *Age* and *Education* to account for differences in aptitude or experience across the participants. Finally, *Female*, *Ethnicity*, and *ESL* control for any differences that may be associated with gender or ethnicity.

Results. Table 8 presents the results of our estimation of Equation 2, which tests whether the participant’s level of understanding of the game is related to making choices which are predicted by either refinement. Model (1) tests for consistency with the Undefeated refinement’s predictions and Model (2) tests for consistency with the Intuitive Criterion refinement’s predictions. As shown in Model (1) of Table 8, participants reporting a high level of understanding of the game were more likely to make choices consistent with the Undefeated refinement than participants reporting a low level of understanding of the game (coeff 0.68, $p < 0.05$, odds ratio [OR] = 1.97). This effect corresponds to a 0.66 predicted probability of making a choice consistent with the Undefeated refinement for participants with a high self-reported understanding of the game (*Understanding* = “1”) versus 0.51 for participants with a low self-reported understanding of the game (*Understanding* = “0”).¹⁵ From Model (2), participants reporting a high level of understanding of the game were less likely to make choices consistent with the Intuitive Criterion refinement than participants reporting a low level of understanding of the game (coeff -0.91, $p < 0.001$, OR = 0.40). This effect

¹⁵This is the average marginal effect (AME) of *Understanding* over all observations.

corresponds to a 0.19 predicted probability of making a choice consistent with the Intuitive Criterion refinement for participants with a high self-reported understanding of the game ($Understanding = \text{"1"}$) versus 0.35 for participants with a low self-reported understanding of the game ($Understanding = \text{"0"}$). We compare the coefficients on $Understanding$ between Models (1) and (2) and find that the difference is significant (Wald χ^2 22.46, $p < 0.001$), underscoring that participants with a higher understanding of the game were more likely to make choices predicted by the Undefeated refinement than by the Intuitive Criterion refinement.

5.3.2 Impact of Choices on Payoffs

As a further test of the robustness of various strategies, we analyze whether decision making that is consistent with each refinement has an impact on the payoffs participants received.

Measures. Supplementing the variables described above, we utilize a continuous dependent variable, $Payoff$, which captures the payoff the participant received in each round based on their outcome reached between themselves and their paired investor.

Empirical Model. We use the following OLS specification, which we estimate with robust standard errors clustered by participant:

$$\begin{aligned} Payoff_{ij} = & \gamma_0 + \gamma_1 \cdot Undefeated_{ij} + \gamma_2 \cdot Intuitive_{ij} + \gamma_3 \cdot Understanding_i + \\ & \gamma_4 \cdot Understanding - No Response_i + \gamma_5 \cdot Big_{ij} + \gamma_6 \cdot Switch_{ij} + \\ & \xi' X_i + \epsilon_{ij}. \end{aligned} \tag{3}$$

where $Payoff$ is the payoff for the participant in each round. The other variables and vector of controls are as described for Equation (2). By comparing the payoffs earned by firms making decisions that are consistent with each refinement, we are able to investigate which set of strategies is more rational for the profit maximizing firm. To the extent that a choice associated with one refinement methodology is more profitable in our experimental market than a choice consistent with the other, we would assert that an actual firm, helmed by actual decision makers and facing a real, dynamic market, may have incentives to make such choices in practice.

Results. Table 9 presents the OLS estimation of Equation 3 specifying the relationship between the participants' payoffs and whether their choices were consistent with either the Intuitive Criterion

or Undefeated refinements. Model (1) includes both *Undefeated* and *Intuitive* in the specification while Models (2) and (3) examine them separately. We estimate each model using OLS with robust standard errors clustered by participant. In model (1), the coefficient on *Undefeated* is positive and significant (coeff 0.04, SE 0.01, $p < 0.01$) and the coefficient on *Intuitive* is negative and significant (coeff -0.05, SE 0.01, $p < 0.001$). A Wald test comparing these coefficients provides evidence that participants who make choices that are predicted by the Undefeated refinement receive a higher payoff than those making choices predicted by the Intuitive Criterion refinement (difference 0.088, Wald χ^2 67.37, $p < 0.001$). This \$0.088 difference is economically material, representing an average 11.3% increase in the payoff earned by participants when their choice is consistent with the Undefeated refinement rather than the Intuitive Criterion refinement. Recall that none of the choices available to the firm in any round are dominated by any other choice, so the firm is not guaranteed to make more money by making choices that conform to any particular refinement. Instead, the payoffs earned by the firm are in part determined by the actions, and hence the beliefs, of the investors in each round of the game. A higher payoff implies that investors are awarding higher valuations to firms when their choices are consistent with the Undefeated refinement.

6 Applications of the Undefeated Refinement

Signaling game theory has been used to analyze how parties will behave in the face of information asymmetry in a variety of situations relevant to operations management. As shown in Section 5.2, conformance to pooling or separating outcomes is dependent on the utility payoffs. We argue that this dependence enables our results to be generalized to other settings where rational and self-interested players are making utility-maximizing decisions. In this section, we examine how the results of Cachon and Lariviere (2001), the most widely cited signaling game paper in the operations management literature, can be extended by considering pooling PBE outcomes which exist and survive the Undefeated refinement.

6.1 Supply Chain Coordination in Cachon and Lariviere (2001)

Cachon and Lariviere (2001) evaluate demand forecast sharing between a manufacturer (she/her) and a supplier (he/his). The authors analyze the impact of asymmetric information between the manufacturer and supplier and identify how the manufacturer can develop contract terms that

signal her private demand information to the supplier. We focus our discussion on the voluntary compliance regime described in the paper as this is the case in which the manufacturer faces a signaling problem and must employ a costly signal to convince the supplier to build the desired capacity.

The authors concentrate on the separating equilibrium, but acknowledge that “there might exist one or more pooling equilibria in which the supplier assumes that both [manufacturer] types offer the same terms” (Cachon and Lariviere 2001, p.642). Noting that the analysis of such equilibria is complex, they “defer the analysis of pooling equilibria to future research.” We apply the Undeclared refinement to highlight how the analysis in this paper can be extended to include pooling equilibria, as envisioned by the authors. Using the Undeclared refinement provides three additional benefits. First, it provides a tractable analytical framework for an otherwise complex problem. Second, it allows for the identification of conditions under which the different equilibrium outcomes (pooling versus separating) are expected. Third, it facilitates an analysis of player actions under these different equilibrium outcomes.

We adopt the authors’ notation and summarize important aspects of the model here, though the reader should refer to the original manuscript for details. The manufacturer faces stochastic demand and knows some parameter θ of its demand distribution such that $D_\theta = \theta X$, where X is a random variable with cumulative distribution function F and $\theta \in \{L, H\}$ with $F(x|L) > F(x|H)$ for $x > 0$ and $F(0|L) \geq F(x|H)$. The supplier is unaware of the manufacturer’s θ due to information asymmetry, but everything else in the model is common knowledge. The expected sales given an available capacity K is $S_\theta(K) = K - \int_0^K F_\theta(x) dx$. It costs the supplier $c_K > 0$ to install one unit of capacity and $c_p > 0$ to produce one component for the manufacturer. The manufacturer includes the supplier’s component in her finished product, which she sells for $r > c_K + c_p$ per unit.

The sequence of events is as follows. The manufacturer learns her demand distribution D_θ and the supplier learns the probability $\rho \in (0, 1)$ that the true demand distribution follows D_H and $1 - \rho$ that it follows D_L . The manufacturer offers a contract to the supplier to induce him to build capacity K . The supplier accepts the contract if it provides him with an expected profit greater than zero. Upon acceptance, the supplier decides how much capacity to build. Demand is then realized and profits are earned.

The contract offered by the manufacturer may include both firm commitments and options,

where $m \geq 0$ is the number of firm commitments and $o \geq 0$ is the number of options. The supplier is paid w_m per firm commitment, w_o per option, and w_e per option exercised and delivered. For notational convenience, the authors use w_θ in place of w_e to reflect different wholesale prices offered by the two manufacturer types, where $w_\theta(K) = \frac{c_K}{F_\theta} + c_p$.

The manufacturer's profits depend on her type, the contract terms, the amount of capacity, and the supplier's beliefs about her type. K_H^* (K_L^*) denotes that capacity which maximizes the high (low) type manufacturer's expected profits when there is no information asymmetry. Under information asymmetry, the expected profit using a wholesale price-only contract for a type θ manufacturer if the supplier believes the manufacturer is type $\tau \in \{L, H\}$ is:

$$\Pi_\theta(K, \tau) = (r - w_\tau(K)) S_\theta(K). \quad (4)$$

The authors show that the high type manufacturer has multiple contract alternatives to credibly reveal her type to the supplier, all of which yield a separating PBE. One option is to purchase K_H^* options at a price of $w_o = A/K_H^*$, where A is effectively a lump sum paid to the supplier, $A = \Pi_L(K_H^*, H) - \Pi_L(K_L^*, L)$. Another option, which produces a higher expected profit for the high type, is to signal with the wholesale price by requesting $K > K_H^*$ and offering a smaller lump sum. Finally, the authors point out that firm commitments are more effective than a lump sum payment. In this case, when a type θ manufacturer who the supplier believes to be type H pays a lump sum A and buys m firm commitments at $w_m = W_H(K)$, the expected profit is:

$$\Pi_\theta(K, m, A) = rS_\theta(K) - w_H(K) (S_\theta(K) - S_\theta(m) + m) - A, m \leq \bar{m}_H(K). \quad (5)$$

where $\bar{m}_H(K)$ is an upper bound on m necessary to ensure the supplier builds some capacity.

6.2 Allowing for Pooling PBE

We generalize these results to account for a pooling PBE that survives the Undeclared refinement. We utilize some additional notation to present these results. Let g denote the posterior probability that the manufacturer is a high type and $1 - g$ denote the posterior probability that she is a low type. Let $F_P = gF_H + (1 - g)F_L$ denote the supplier's perception of the cumulative distribution function for demand when the supplier is unaware of the manufacturer's type. In a pooling PBE $g = \rho$ and both manufacturer types offer the same contract terms. Finally, let K^P be the capacity

investment that maximizes the expected utility of a high type in a pooling PBE, i.e.,

$$K^P = \arg \max_K \Pi_H(K, m, A) : (g = \rho). \quad (6)$$

We consider pooling PBE in which both manufacturer types offer the same wholesale price-only contract and compare this to separating PBE alternatives in which the manufacturer is free to use some combination of pricing, firm commitments and lump sum payments. This is conservative as additional pooling PBE may exist in which both manufacturer types offer the same combination of pricing, firm commitments and lump sum payments. We leave this extension to future research. To account for the fact that in a pooling PBE the supplier does not know the firm's type, we modify Equation (4) to:

$$\Pi_\theta(K, g) = (r - w_g(K)) S_\theta(K), \quad (7)$$

where $w_g(K) = \frac{c_K}{F_P} + c_p$. Note that when $g = 1$, we recover Equation (4) for $\tau = H$, and when $g = 0$ we recover Equation (4) for $\tau = L$.

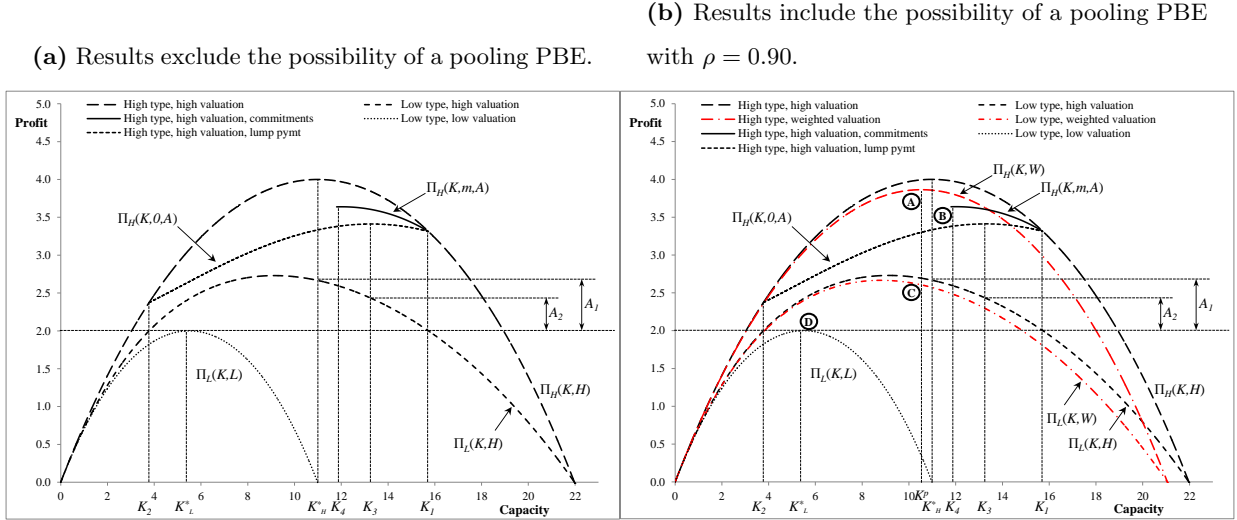
A pooling PBE will exist in which the manufacturer, regardless of her type, chooses capacity K^P and offers w_g , provided $\Pi_H(K, g) > \max_{K, m, a} \Pi_H(K, m, A)$ and $\Pi_L(K, g) > \Pi_L(K_L^*, L)$. These conditions are also sufficient for the pooling PBE at K^P to survive the Undeclared refinement. The intuition behind this result is that both types will pool at K^P if doing so yields a strictly higher expected profit than could otherwise be achieved under the best possible separating PBE outcome.

6.3 Example

We use the example in Section 5.4 of Cachon and Lariviere (2001) to demonstrate that a pooling PBE will provide a superior return for both manufacturer types (and therefore survive the Undeclared refinement) compared to the best separating PBE alternative. In this example, demand is exponentially distributed with mean $\theta_H = 10$ for the high type manufacturer and $\theta_L = 5$ for the low type, $r = 1$, $c_K = 0.1$ and $c_p = 0.1$. Figure 4a identifies the manufacturer's profit curves and corresponds to Figure 1 in Cachon and Lariviere (2001). The main findings from the original example are that a high type manufacturer can separate either by using a wholesale price-only contract at K_H^* and paying a lump sum $A_1 = 0.67$, offering K_3 and a lump sum $A_2 = 0.43$, or offering K_4 and firm commitments of $m = 2.65$. The high type receives the highest expected profit of 3.65 under last option while the low type receives an expected profit of 2.00 under each option.

Figure 4b introduces the expected profit curves for both manufacturer types under a pooling PBE using Equation (7) for $g = \rho$. The expected profit for the high type at K^P is 3.86 (labeled as Point A in the figure), which represents an improvement of 6% compared to the high type's best separating PBE outcome of 3.65 in Cachon and Lariviere (2001) (labeled as Point B). The expected profit for the low type at K^P is 2.61 (labeled as Point C), which represents a 30% improvement compared to the low type's separating PBE outcome of 2.00 in Cachon and Lariviere (2001) (labeled as Point D). The pooling PBE at K^P offers materially higher expected profits for the manufacturer regardless of her type. This outcome also has implications for the supplier and the supply chain. The supplier's expected profits are reduced by 0.30 compared to the best separating outcome identified in Cachon and Lariviere (2001). This reduction in expected supplier profits in the pooling outcome is primarily because the high type manufacturer no longer pays a firm commitment to the supplier to reserve potentially unneeded capacity. The net effect is that the total expected supply chain profits increase by 0.08, or 1.7%.

Figure 4: Manufacturer's Profit as a Function of Capacity with Exponential Demand Under Voluntary Compliance.



In our example we assumed $\rho = 0.90$, but the pooling PBE outcome is not idiosyncratic to this particular value of ρ . Both types will achieve a higher expected profit from pooling for any $\rho \in [0.75, 1.0)$.

6.4 Applications to Other Research

We note that the results of other research streams can be extended by explicitly considering pooling outcomes through the application of the Undefeated refinement. These research streams include supply chain coordination and contracting (Özer and Wei 2006), franchising decisions (Desai and Srinivasan 1995), channel stuffing (Lai et al. 2011), and market encroachment by suppliers (Li et al. 2014). The outcome examined in each of these papers is the least cost separating PBE. In each case, however, a pooling PBE exists and survives the Undefeated refinement across some set of model parameters. We leave a detailed analysis of the implications of applying the Undefeated refinement in these settings to future research.

7 Opportunities for Future Research

Our experimental analysis is intended to test the predictive power of common equilibrium assumptions made in signaling games, not to provide a behavioral explanation of why some equilibrium assumptions are more predictive than others. It may be that decision makers are influenced by behavioral factors that align with the predictions of the Undefeated refinement. Behavioral explanations may include the use of cognitive hierarchy models (Camerer et al. 2004), payoff disparity comparisons (Ho and Weigelt 1996), or risk seeking and risk aversion tradeoffs (Holt and Laury 2002). Developing a better understanding of the behavioral mechanisms that lead to certain decisions under information asymmetry will not only provide insights into the boundary conditions on when the various refinements are more appropriate, but may also lead to the development of improved equilibrium refinement assumptions. We leave this investigation for future research.

8 Implications and Conclusions

Our findings provide the first evidence that when pooling equilibria exist, they can be more predictive of operations management decisions made under information asymmetry than the more commonly studied least cost separating equilibria. The predicted outcomes in our setting, and from signaling game models generally, can yield materially different results and are sensitive to equilibrium assumptions, specifically whether the Undefeated refinement or the Intuitive Criterion refinement is applied. Testing the predictive power of these assumptions is therefore important.

While decision making under information asymmetry is a burgeoning field within operations management, little has been done to reconcile the assumptions that underlie models in this area with the choices of actual decision makers. The primary contribution of this paper is to provide empirical evidence that characterizes the types of decisions made by actors in these contexts. In our experiment, pooling outcomes, which are not regularly considered in the literature, were widespread among participants, relative to separating outcomes. In particular, averaged across all scenarios, participant choices were three times more likely to conform with the Undefeated refinement, which allows for pooling equilibria, than the Intuitive Criterion refinement, which does not, and to date has been the predominant belief refinement used in the operations management literature. These results can inform the development of operations management theory, as well as help practitioners interpret the implications of models that emerge from our field.

We observe several patterns in our data that provide confidence that the conformance with the Undefeated refinement that we observe in the laboratory may extend to the decision-making choices of real managers. First, we expect that prudent managers would make deliberate decisions in practice, paying attention to changing dynamics and responding rationally to changes in the underlying payoff structure. We observe such actions in our experiment, wherein participants' decisions corresponded with changes in the underlying newsvendor unit price, which suggests that participants were paying attention to the stimuli and being thoughtful about their decisions. Second, in practice, we expect actual decision makers to possess a deep understanding of the decision space and the implications of their decisions. Consistently, in our experiment, we observe that participants who report a high level of understanding of the setting are significantly more likely to make choices that are consistent with the Undefeated refinement than participants who report a low level of understanding. Third, we expect managers to use strategies that generate higher payoffs. In our experiment, participants who made choices that were consistent with the Undefeated refinement earned higher payoffs from investors on average than participants who made choices that were consistent with the Intuitive Criterion refinement. This is particularly interesting in the context of our experiment, in which participants engaged in decisions from both the investor and firm perspectives and were exposed to the full set of incentives afforded to both sides. Finally, we would expect that over time, experienced managers would increasingly gravitate toward the strategy that returns the highest payoff. Indeed, in our experiment, while participant choices overwhelmingly

conformed with the predictions of the Undeclared refinement, even during the first rounds of game play, the tendency to make such choices intensified as participants experienced more rounds of the game. As the order in which scenarios were presented was counterbalanced across sessions, the pattern of these results is consistent with participants learning the efficacy of various strategies and converging on the most successful strategies over time. All of these patterns observed among the participants in our experiment are consistent with the actions of managers in practice, which increases our confidence about the generalizability of our results.

Managers are constantly operating under conditions of information asymmetry. The decisions they make can send signals about their firms' prospects to less-informed parties in a broad array of contexts. From a manager evaluating the viability of a potential supply chain partner, to a customer evaluating a firm's ability to meet her needs, to an analyst developing guidance on a firm's future stock performance, the signals firms send through their actions can materially influence how they are perceived and engaged by less-informed parties, with important implications for both sides. We expect this growing area of operations management research to continue to flourish. To the extent our results expand the set of anticipated managerial choices in these contexts, exploring their operational implications through the application of the Undeclared refinement may enrich the extant theory. Opportunities exist to revisit established models, explore the implications of equilibrium assumptions in new settings, and empirically examine managerial decisions and outcomes under information asymmetry. Furthermore, future experimental work may unpack the behavioral drivers underlying various equilibria among the parties in these settings, as well as their corresponding boundary conditions. We leave these promising lines of inquiry to future research.

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Table 1: The model parameters used to generate the six scenarios in the experiment.

Scenario	μ_S	μ_B	σ^2	p	b	w	β	$1 - \lambda$	Q
1	6.0	6.25	0.15	0.75	0.05	0.40	0.60	0.35	100
2	6.0	6.25	0.15	0.80	0.05	0.40	0.60	0.35	100
3	6.0	6.50	0.15	0.75	0.05	0.40	0.60	0.35	200
4	6.0	6.50	0.15	0.80	0.05	0.40	0.60	0.35	200
5	6.0	6.25	0.15	0.85	0.00	0.40	0.55	0.35	100
6	6.0	6.25	0.15	0.90	0.00	0.40	0.55	0.35	100

Table 2: Summary of the Undeclared refinement and Intuitive Criterion refinement predictions for each scenario.

	Scenario:					
	1	2	3	4	5	6
Undeclared	Pool on 5	Pool on 5	Pool on 6	Pool on 6	Pool on 5	Pool on 5
Intuitive Criterion	Separating	Separating	Separating	Separating	Separating	Separating

Table 3: Distribution of participants for categorical variables

Education Level	Frequency	Percent
High School	21	9.21
Some College	114	50.00
Bachelor's	48	21.05
Graduate / Professional	41	17.98
Other / Missing	4	1.75
Total	228	100
Ethnicity	Frequency	Percent
African American	33	14.47
Asian	46	20.18
Caucasian	107	46.93
Hispanic	18	7.89
Other / Missing	24	10.53
Total	228	100
Session	Frequency	Percent
1	34	14.91
2	36	15.79
3	36	15.79
4	36	15.79
5	30	13.16
6	32	14.04
7	24	10.53
Total	228	100

Table 4: The proportion of participant decisions predicted by the Undeclared and Intuitive Criterion refinements.

	<u>Scenario:</u>						
	1	2	3	4	5	6	Total
Undeclared	71.1%***	59.7%***	63.2%***	55.7%***	71.1%***	60.5%***	63.5%***
Difference		11.4%*		7.5%		10.5%*	
Intuitive Criterion	17.1%***	29.4%	17.1%***	25.9%*	15.8%***	20.6%***	20.9%***
Difference		-12.3%**		-8.8%*		-4.8%	
Observations	228	228	228	228	228	228	1,368

Notes: The percentages in row 1 identify the proportion of participants whose choices conform to the Undeclared refinement. The percentages in row 2 are the difference between the percentages in row 1 for scenarios 1 and 2, 3 and 4, and 5 and 6. The percentages in row 3 identify the proportion of participants whose choices conform to the Intuitive Criterion refinement. The percentages in row 4 are the difference between the percentages in row 3 for scenarios 1 and 2, 3 and 4, and 5 and 6. The symbols in rows 1 and 3 identify whether the values are statistically significantly different from 33.333%. The symbols in rows 2 and 4 identify whether the values are statistically significantly different from 0%. All test are made using two-tail binomial tests with *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and + $p < 0.10$.

Table 5: The proportion of participant decisions which comply to the Undeclared refinement, differentiated by firm type.

	<u>Scenario:</u>					
	1	2	3	4	5	6
“Big” Type	68.9%***	49.6%***	61.5%***	47.3%***	64.0%***	53.8%***
Difference		19.3%***		14.2%*		10.2%+
Observations	148	141	148	150	150	158
“Small” Type	75.0%***	75.9%***	66.3%***	71.8%***	84.6%***	75.7%***
Difference		0.9%		-5.5%		8.9%
Observations	80	87	80	78	78	70

Notes: The percentages in row 1 identify the proportion of “Big” type firms whose choices conform to the Undeclared refinement. The percentages in row 2 are the difference between the percentages in row 1 for scenarios 1 and 2, 3 and 4, and 5 and 6. The percentages in row 4 identify the proportion of “Small” type firms whose choices conform to the Undeclared refinement. The percentages in row 5 are the difference between the percentages in row 4 for scenarios 1 and 2, 3 and 4, and 5 and 6. The symbols in rows 1 and 4 identify whether the values are statistically significantly different from 33.333%. The symbols in rows 2 and 5 identify whether the values are statistically significantly different from 0%. All test are made using two-tail binomial tests with *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and + $p < 0.10$.

Table 6: Description of Variables

Variable	Description
<i>Undeclared</i>	Indicator variable identifying whether the Undeclared refinement predicts the firm’s choice (‘1’) or not (‘0’)
<i>Intuitive</i>	Indicator variable identifying whether the Intuitive Criterion refinement predicts the firm’s choice (‘1’) or not (‘0’)
<i>Payoff</i>	Payoff (in dollars) the participant received in the round
<i>Understanding</i>	Indicator variable identifying whether the participant rated their understanding as a ‘5’ or higher (‘1’), or a ‘4’ or lower (‘0’) on a 7-point Likert scale where ‘1’ indicates “I did not understand the game at all” and ‘7’ indicates “I understood the game completely”
<i>Understanding - No Response</i>	Indicator variable identifying whether the participant rated their understanding (‘1’) or not (‘0’)
<i>Big</i>	Indicator variable identifying whether the participant’s firm is a Big type in current round (‘1’) or a Small type (‘0’)
<i>Switch</i>	Indicator variable identifying whether the participant’s final choice deviates from their initial strategy (‘1’) or not (‘0’)
<i>Session</i>	Categorical variable identifying the experimental session
<i>Sequence</i>	Categorical variable identifying the sequence in which a scenario was presented to the participant
<i>Age</i>	Participant’s age
<i>Female</i>	Indicator variable identifying whether the participant is female (‘1’) or male (‘0’)
<i>Ethnicity</i>	Categorical variable indicating whether the participant is African-American, Asian, Caucasian, Hispanic, Pacific Islander, or Other
<i>Education</i>	Categorical variable indicating whether the participant has a high school diploma, some college, a bachelors degree, or an advanced degree
<i>ESL</i>	Indicator variable identifying whether English is participant’s second language (‘1’) or primary language (‘0’)

Notes: *Understanding*, and demographic variables (*Age* through *ESL*) are dimensioned by participant. All other variables are dimensioned by participant-round.

Table 7: Summary Statistics and Correlations

Variables	Mean	Std. Dev.	Min.	Max.	N	Undeclared	Intuitive	Payoff	Understanding	Big	Switch	Age	Female	ESL
Undeclared	0.64	0.48	0	1	1368	1.00								
Intuitive	0.21	0.41	0	1	1368	-0.68	1.00							
Payoff	0.85	0.21	0.02	1.27	1368	0.06	-0.12	1.00						
Understanding	0.86	0.35	0	1	1368	0.14	-0.16	0.07	1.00					
Big	0.65	0.48	0	1	1368	-0.17	0.07	0.51	0.02	1.00				
Switch	0.11	0.31	0	1	1368	-0.12	0.05	-0.02	-0.07	-0.04	1.00			
Age	25.43	9	18	63	1278	-0.15	0.18	-0.04	-0.15	0.02	-0.04	1.00		
Female	0.48	0.5	0	1	1362	0.00	-0.03	-0.01	-0.08	-0.04	0.06	-0.16	1.00	
ESL	0.11	0.31	0	1	1362	-0.00	0.03	-0.00	-0.02	-0.05	-0.08	0.03	-0.00	1.00

Table 8: Estimating whether the predictive powers of the Undeclared and Intuitive Criterion refinements are associated with the participant’s self-reported *Understanding* of the game.

Dependent Variable:	(1) <i>Undeclared</i>		(2) <i>Intuitive</i>	
	Coefficient	OR	Coefficient	OR
<i>Understanding</i>	0.68* [0.28]	1.97* [0.56]	-0.91*** [0.27]	0.40*** [0.11]
<i>Understanding - No Response</i>	-0.50 [0.94]	0.61 [0.57]	-1.61+ [0.94]	0.20+ [0.19]
<i>Big</i>	-0.93*** [0.17]	0.39*** [0.07]	0.42* [0.19]	1.52* [0.29]
<i>Switch</i>	-0.83*** [0.22]	0.44*** [0.10]	0.44+ [0.23]	1.56+ [0.36]
Constant	1.01* [0.48]	2.74* [1.33]	-1.25* [0.51]	0.29* [0.15]
Observations	1,368		1,368	
Pseudo R^2	0.11		0.09	
Mean DV	0.64		0.21	
Hosmer and Lemeshow χ^2	12.63		5.94	
Hosmer and Lemeshow p-value	0.13		0.65	
Wald χ^2			22.46***	

Notes: Logistic estimation with robust standard errors clustered by participant in brackets. Included controls – *Session*, *Sequence*, *Age*, *Female*, *Ethnicity*, *Education*, and *ESL*. The Hosmer and Lemeshow χ^2 test is based off of 10 groupings of the predictor variables. A large p-value for this test indicates a good model fit. Wald χ^2 provides a test of the equivalency of the coefficient on *Understanding* across models (1) and (2). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Table 9: Estimating whether the participant’s payoff depends on their choice being predicted by the Undeclared refinement or the Intuitive Criterion refinement.

Dependent Variable: <i>Payoff</i>		(1)
(A)	<i>Undeclared</i>	0.04** [0.01]
(B)	<i>Intuitive</i>	-0.05*** [0.01]
	<i>Understanding</i>	0.01 [0.01]
	<i>Understanding - No Response</i>	-0.02 [0.03]
	<i>Big</i>	0.23*** [0.01]
	<i>Switch</i>	0.02 [0.01]
	Constant	0.62*** [0.02]
Observations		1,368
R^2		0.38
Mean DV		0.85
Wald F : (A)-(B)=0?		67.37***

Notes: OLS estimation with robust standard errors clustered by participant in brackets. Included controls – *Session*, *Sequence*, *Age*, *Female*, *Ethnicity*, *Education*, *Student*, and *ESL*. Wald tests report F statistics. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Appendix

Extensive Form Representations

Figure 5: Extensive form of Scenarios 3 and 4.

(a) Firm and investor payoffs for Scenario 3. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a “Small” opportunity type firm.

(b) Firm and investor payoffs for Scenario 4. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a “Small” opportunity type firm.



Figure 6: Extensive form of Scenarios 5 and 6.

(a) Firm and investor payoffs for Scenario 5. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a “Small” opportunity type firm.

(b) Firm and investor payoffs for Scenario 6. There is a 35% probability that the participant in the role of the firm is randomly assigned to be a “Small” opportunity type firm.



Participant Instructions Script

The script read to all participants in the experiment is below.

Slide 1. Welcome. I will first take you through an overview of the game that you will play and then walk you through an example that will describe exactly how you will play this game on the computer.

Slide 2. In each round you will be randomly assigned to play either the role of a Firm or an Investor. Firms and Investors will then be randomly and anonymously paired with different people in each round.

Slide 3. Firms will either have a “Small” or “Big” market opportunity, which is just a measure of the number of customers the Firm expects to have for its product or service. Both the Firm and Investor will know the Firm’s likelihood of getting a “Small” or “Big” market opportunity, but only the Firm will know for sure its actual opportunity.

Slide 4. Knowing its market opportunity, the Firm will decide how many stores to open. The Firm’s payoff depends not only on this decision, but on the price the Investor sets for the Firm.

Slide 5. The Investor learns how many stores the Firm will open and sets a price for the Firm. The Investor’s payoff depends on setting a price close to the Firm’s actual value.

Slide 6. You will see a picture similar to this in each game you play. I will cover the information on this picture. As I mentioned previously, in each round the Firm is randomly assigned either a “Big” market opportunity or a “Small” market opportunity.

Slide 7. The Firm has three choices for the number of stores to open, depending on its market opportunity. In this example, a “Big” opportunity Firm can choose to open 6, 7 or 8 stores while a “Small” opportunity Firm can choose to open 5, 6, or 7 stores. Note that your information is always in red and the other player’s information is in blue.

Slide 8. Depending on the Firm’s choice, the Investor has either no choice or three choices for what price to set for the Firm. In this example, only a Firm with a “Big” opportunity can open 8 stores, and only Firm with a “Small” opportunity can open 5 stores. Note that both a “Big” and a “Small” opportunity Firm can open either 6 or 7 stores. If the Investor sees one of these choices the Investor must decide whether to set a “Big”, “Small” or “Weighted” price to the Firm. A “Weighted” price is a weighted average price.

Slide 9. If you are a Firm, your payoff depends on the size of the opportunity, your store choice, and the price the Investor sets. In this example, if a “Big” Firm chooses 8 stores it will get a payoff of \$0.82. If, however, a “Big” Firm chooses 6 stores it will get a payoff of \$1.08, \$0.98 or \$0.77 depending on whether the Investor sets a price of “Big”, “Weighted” or “Small”. Similarly, if a “Big” Firm chooses 7 stores it will get a payoff of \$1.00, \$0.88 or \$0.62 depending on whether the Investor sets a price of “Big”, “Weighted” or “Small”.

Slide 10. If you are an Investor, your payoff depends on setting a price close to the Firm’s actual value. For instance, in this example if the Firm chooses 6 stores and the Investor sets a price of “Big”, the Investor will receive a payoff of \$1.00 if the Firm is “Big,” and a payoff of \$0.34 if the Firm is instead “Small”.

Slide 11. When the game begins, you will be told on screen whether you are a Firm or an Investor and the chance the Firm has of getting a “Big” or “Small” market opportunity. You will see a graphic with the choices and payoffs for your game. Firms and Investors will receive the same information and will be asked to define their strategies. If you are a Firm, you will be asked “If you faced a Big market opportunity, how many stores would you open?” and “If you faced a Small market opportunity, how many stores would you open?”

Slide 12. If you are an Investor, you will be asked “If the Firm opened X stores, what price would you give them?”

Slide 13. The Firm’s market opportunity is then randomly assigned and the Firm confirms their store quantity choice.

Slide 14. The Investor sees the Firm’s store quantity choice and confirms the price they want to give to the Firm.

Slide 15. The Firm and Investor learn what their pay-outs are for the previous game. Firms and Investors swap roles. Firms and Investors are randomly assigned to new partners. Firms are randomly assigned a “Big” or “Small” opportunity and a new game begins with different choices and/or pay-outs.

Slide 16. In addition to your show-up fee, you will be paid the sum of all your individual payoffs from the money rounds at the end of today’s session. You should try to make as much money as possible. You are not taking money from other players. You are playing with other people, and they can’t move forward unless you move forward. Please make your decisions in a timely fashion, be thoughtful but move quickly. If your screen is black it means you are waiting for another player to make a decision. One other thing, please don’t close your browser, or press next, back or refresh on the browser, as this can disrupt the game. If you have any questions during the practice rounds, please raise your hand, and one of us will come around and answer your question. Thank you! You may now begin.