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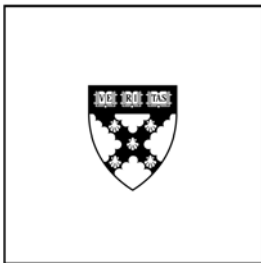
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Decision Making Under Information Asymmetry: Experimental Evidence on Belief Refinements

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July 20, 2014

Abstract

We explore how individuals make decisions in an operations management setting when there is information asymmetry between the firm and an outside investor. A common assumption in the signaling game literature is that beliefs among the participants in the game are refined using the Intuitive Criterion refinement. Our experimental results provide evidence that the predictive power of this refinement is quite low, and that the Undeclared refinement better captures actual choice behavior. This is surprising because the Intuitive Criterion refinement is the most commonly utilized belief refinement in the literature while the Undeclared refinement is rarely employed. Our results have material implications for both research and practice because the Undeclared and Intuitive Criterion refinements often produce divergent predictions. Our results demonstrate that conformance to the Undeclared and Intuitive Criterion refinements is influenced by changes in the underlying newsvendor model parameters. We also show that adherence to the Undeclared refinement is especially pronounced among subjects who report a high level of understanding of the game and that subjects whose choices conformed with the predictions of the Undeclared refinement were rewarded by investors with higher payoffs in the game. Finally, we demonstrate, through a reexamination of Cachon and Lariviere (2001), how the application of the Undeclared refinement can substantively extend the implications of extant signaling game theory in the operations management literature.

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1 Introduction

Managers are often required to make decisions in settings with information asymmetry, including new product introductions (Lariviere and Padmanabhan 1997), competitive entry (Anand and Goyal 2009), supplier contracts (Cachon and Lariviere 2001), and capacity investments (Lai et al. 2012). Although game theorists have created a variety of tools to aid in the analysis of such decisions, these tools can produce an abundance of justifiable outcomes. Unfortunately, having a model that predicts that anything can happen is about as useful for practical decision making as having no model at all. To address this, researchers have developed an assortment of refinement mechanisms that pare down the set of equilibrium outcomes by imposing assumptions about how participants in the decision setting form their beliefs. Not only can different refinements produce dramatically different predicted outcomes, they may also have different predictive power in practical operations management settings. Despite this, the question of which refinement mechanisms to employ has received little attention in the operations management literature. This is surprising given the wide range of applied issues that game theory has been used to study in operations management.

To shed light on this issue, we examine whether decision makers' choices conform to the predictions of different refinement mechanisms through a controlled experiment in a context relevant to operations management – a capacity expansion decision. We analyze a setting between a manager of a firm (hereafter, the firm) and an equity holder of the firm (hereafter, the investor). As detailed in Section 3.1, the firm faces stochastic demand which can be either “Big” or “Small”. The quality of the demand is revealed to the firm but not to the investor due to information asymmetry between them. The firm is interested in both its long-term performance and the short-term share price set by the investor. The investor is interested in setting a short-term share price that is as accurate as possible. The firm moves first by making a store capacity decision which may provide the investor with information about the true nature of the firm's demand. There is abundant empirical evidence that firms facing short-term investor pressures manipulate long-term investments, including property, plant and equipment (Kedia and Philippon 2009), capital expenditures (McNichols and Stubben 2008), and research and development (Dechow and Sloan 1991, Bushee 1998).

We focus on testing the predictive power of two sets of refinement mechanisms. The first is based generally on equilibrium dominance and represented by the Intuitive Criterion refinement.

The second is based on Pareto optimization logic and represented by the Undeclared refinement. The assumptions reflected in our experiment¹ are commonly used in the signaling game literature (Kreps and Sobel 1992). The predicted outcomes in our experiments, and from signaling game models generally, are sensitive to whether the Undeclared refinement or the Intuitive Criterion refinement is applied. The choice of which refinement to employ is at the discretion of the researcher, underscoring the importance of the contribution we make in testing the practical validity of the different outcomes predicted by these refinement methods.

Our findings represent a significant contribution to the literature as they provide the first evidence that the Undeclared refinement is more predictive of operations management decisions made under information asymmetry than the more commonly applied Intuitive Criterion refinement. This result is accentuated among participants who report a high level of understanding of the game. Furthermore, participants whose decisions are congruent with the predictions of the Undeclared refinement earn higher payoffs from investors than those whose decisions are congruent with the predictions of the Intuitive Criterion refinement. We also show that subject conformance to these refinements is sensitive to changes in the underlying newsvendor model parameters. Finally, we highlight some of the implications for the operations management literature by detailing in Section 7 how the insights from Cachon and Lariviere (2001) can be expanded upon through the application of the Undeclared refinement.

2 Literature Review

Our experimental examination of how people behave under information asymmetry builds on two streams of scholarship, as described below.

2.1 Empirical Evidence for Deviations from Model-Based Rules

We contribute to a broad literature that seeks to explain why managers make operational decisions that do not maximize long-term expected profits. Deshpande et al. (2003) and van Donselaar et al. (2010) use large sample observational data to show that decisions in practice differ from those which would theoretically maximize the firm's performance. Several experimental studies have identified that decision makers may deviate from the expected-profit-maximizing capacity choice

¹Two players, one costly signal, two types of the informed player, and the single crossing property holds.

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). Although the payoffs in our experiment are developed using the newsvendor model, subjects are not directly exposed to the newsvendor model. As a result, our research identifies another possible explanation for suboptimal investment levels in practical settings. Specifically, we explore how decision makers behave when information asymmetry exists and managers have utility functions that are influenced by short term share-price concerns.

There is abundant empirical evidence that suggests that firms manipulate investment levels in the presence of information asymmetry with investors. Evidence of such manipulations have been found with both long-term investments, such as capital expenditures (McNichols and Stubben 2008) and research and development (Dechow and Sloan 1991, Bushee 1998, Roychowdhury 2006), as well as shorter-term investments, such as inventory levels (Thomas and Zhang 2002) and maintenance expenditures (Roychowdhury 2006). These papers suggest that such deviations in investment levels can be attributed to managerial efforts to manipulate current period earnings, but the evidence is inconclusive. For instance, Roychowdhury (2006, p.335) simply claims to “find evidence consistent with [earning manipulation]” but does not assert that there is definitive proof. The earnings manipulation explanation is more plausible, however, when investors cannot clearly observe the firm’s investment levels. It is harder to imagine that firms can successfully deceive investors about current period earnings by distorting investment levels when such distortions could be easily detected through regular, audited financial statement reporting. We contribute to this literature by testing how decision makers behave when firms instead use these very visible investment levels as a means to manage the signal information about their type.

2.2 Operations Management Applications of Signaling Game Theory

Operations management researchers have increasingly employed signaling game theory to study the impact of information asymmetry across a variety of topics, 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 capital project and capacity investments (Lai et al. 2012). In all such

cases, the researchers must decide how to address the multiple, and possibly infinite, equilibria that may exist in their models. These equilibrium outcomes are classified as either separating equilibria, in which the low quality firm invests optimally and the high quality firm over-invests in order to signal its quality, or pooling equilibria, in which low quality firms over-invest and high quality firms under-invest so as to provide identical signals to investors (Kreps and Sobel 1992). Cachon and Lariviere (2001), Özer and Wei (2006) and İşlegen and Plambeck (2007) acknowledge that multiple 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.

Other researchers address the issue of multiple equilibria by directly invoking the Intuitive Criterion refinement to refine the beliefs of the participants. Desai and Srinivasan (1995), Lariviere and Padmanabhan (1997), Lai et al. (2011) and Lai et al. (2012) use the Intuitive Criterion refinement to eliminate all possible pooling equilibrium outcomes 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) or more than two players (Anand and Goyal 2009), also employ the Intuitive Criterion refinement, although the refinement may not generate a unique equilibria prediction in these cases. Missing from this research is a consideration of alternative refinement methods, which may yield different predicted outcomes if applied to these models.

The question of which refinement mechanism is most appropriate remains unsettled. Banks et al. (1994) test which refinement subjects 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. Similarly, Brandts and Holt (1992, 1993) consider the predictive power of equilibrium dominance refinements, including the Intuitive Criterion. Other research explores how adaptive learning over repeat play may influence which equilibria subjects 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 testing the predictive power of the Intuitive Criterion refinement against that of the Undeafated refinement, which has not been experimentally tested. The Undeafated refinement has gotten scant attention over the years and

has not been employed in the operations management literature despite its apparent relevance.²

3 Theory

3.1 Model for Player Payoffs

The payoffs in our experiment are theoretically grounded on models employed in Bebchuk and Stole (1993), Lai et al. (2012) and Schmidt et al. (2012). We apply the following set up in Section 4 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 g and type τ_B is denoted $1 - g$, where $g \in [0, 1]$. 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 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 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 . 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 α and $1 - \alpha$ respectively, where $\alpha \in [0, 1]$:

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

A larger value of α 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 by solving the newsvendor model, $\pi(\tau, q) = E_\tau [r \min\{q, x\} + s(q - x)^+ - cq]$ where r is the selling price, c is the purchase cost, and s is the salvage value of unsold inventory; $r > c > s$.

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”

²Google Scholar reports that by the end of 2013 there were 230 citations to Mailath et al. (1993) (which introduced the Undeafated refinement) compared to 2,630 citations to Cho and Kreps (1987) (which introduced the Intuitive Criterion refinement). In addition, there are no citations to Mailath et al. (1993) in Management Science, Operations Research, Manufacturing and Service Operations Management, Production and Operations Management Journal, or Journal of Operations Management.

(which corresponds to $\rho(q) = \pi(\tau_B, q)$), “Weighted” (which corresponds to $\rho(q) = g\pi(\tau_S, q) + (1 - g)\pi(\tau_B, q)$), 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 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 our experimental scenarios, refinements to the players’ out-of-equilibrium (OOE) beliefs can further pare the number of predicted PBE outcomes.

We focus on two particular refinement mechanisms. The first is the Intuitive Criterion refinement, which is based on equilibrium dominance logic. We include it in our analysis because 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 literature³ and arguably the most familiar to operations management researchers.

The second refinement mechanism we test is the Undefeated refinement, which is based on Pareto optimization logic. While not widely employed in the literature, we argue that it may be more appropriate to describe decision outcomes in operations management because it predicts outcomes that result in a Pareto improvement in the firm’s payoff regardless of the firm’s type, and it can be applied in practical settings as a simple heuristic. We describe this heuristic in detail in Section 3.2.2.

³For instance, Riley (2001) notes that the “Intuitive Criterion has dominated the literature in the years since its introduction.”

3.2.1 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” opportunity firm with a higher payoff using the highest valuation the investor could assign but *would* provide a “Big” opportunity 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).

While 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 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), it assumes that counterfactual information can be communicated in the game without being explicitly modeled (Salanie 2005), and it may eliminate all choices from consideration. For an overview of some of the criticisms of the Intuitive Criterion, refer to Mailath et al. (1993), Riley (2001), Bolton and Dewatripont (2005), and Salanie (2005).

3.2.2 The Undefeated Refinement

The Undefeated refinement is based on Pareto-optimization. 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). While not widely adopted, the Undefeated 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 many of the concerns raised about the Intuitive Criterion refinement.

The Undefeated refinement can also be applied as a simple heuristic, which may make it more practically appealing in applied operations management settings. This heuristic is valid even as the game structure gets complex. For instance, under infinite types, infinite strategies, and infinite state spaces, the heuristic 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 compared to 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.

3.3 The Impact of Unit Price on Refinement Compliance

Schmidt et al. (2012) show that changes in the newsvendor model parameters affect the likelihood that a PBE *exists and survives refinement* and the magnitude and direction of this effect depends strongly on whether the Undefeated refinement or Intuitive Criterion refinement is employed. However, *given* that a PBE exists and survives refinement, it is unclear that changes in the newsvendor model parameters will influence whether subjects actually *make choices* which conform to these refinements. There is no accommodation for such influences on behavior in the theory for either refinement. To provide insight on this issue, we directly test whether the predictive power of each refinement varies with perturbations in the underlying newsvendor model parameters.

4 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. (2012). 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

(r) ranges from 0.75 to 1.00 in increments of 0.05, unit salvage value (s) ranges from 0.0 to 0.10 in increments of 0.05, and unit cost is $c = 0.4$. Short-termism (α) 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 (g) 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 made a convenience sample of three scenarios from this set of 4,752 scenarios, and manually confirmed that each scenario satisfies two conditions. First, the scenario must simultaneously test the predictive power of the Undeclared and Intuitive Criterion refinements. To achieve this, we use scenarios with four sequential capacity values based on the capacity increment Q . The first capacity choice 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 choice 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 choice 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 choice must be the least-cost separating capacity for a τ_B type, survive the Intuitive Criterion refinement, and be eliminated by the Undeclared 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 choices. This condition allows us to test the impact on subject behavior 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, an additional three 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 in each scenarios 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).

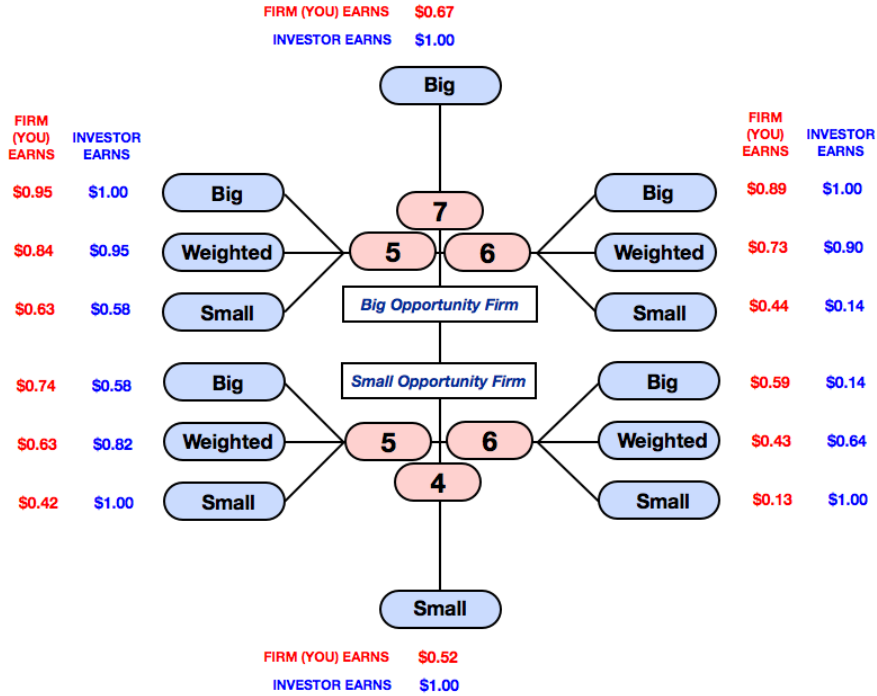
None of the choices in any scenario are strictly dominated, so there is no guarantee that any particular choice will result in a player realizing a higher payoff. A choice is strictly dominated for a firm type if the best utility that firm type could possibly achieve by sending that signal is strictly lower than the worst utility that firm type could possibly achieve by sending some other signal. A PBE has reasonable beliefs if those beliefs do not put a positive probability on any type sending a signal that is strictly dominated. For a technical definition of Strict Dominance, refer to (Mas-Colell et al. 1995, p.469).

Figure 1 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 either 5, 6 or 7 stores, while a "Small" opportunity firm could choose to open either 4, 5, or 6 stores. If the firm chooses to open a pooling quantity of either 5 or 6 stores, then the investor is prompted to decide whether to award the firm a "Small," "Weighted," or "Big" valuation. If instead, the firm chooses a separating quantity of 4 or 7 stores, the investor would be notified of the quantity and informed that the firm must have been a "Small" or "Big" opportunity firm, respectively. The players' payoffs for each outcome are summarized near the terminal node for the outcome.

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 \$0.9045 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 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 survives the Intuitive Criterion refinement since, by construction of the

Figure 1: Extensive form of Scenario 1, with the display formatted for presentation to a firm. There is a 35% probability that the subject in the role of the firm is randomly assigned to be a “Small” opportunity type firm.



Intuitive Criterion refinement, all least cost separating PBE which are not strictly dominated survive 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.

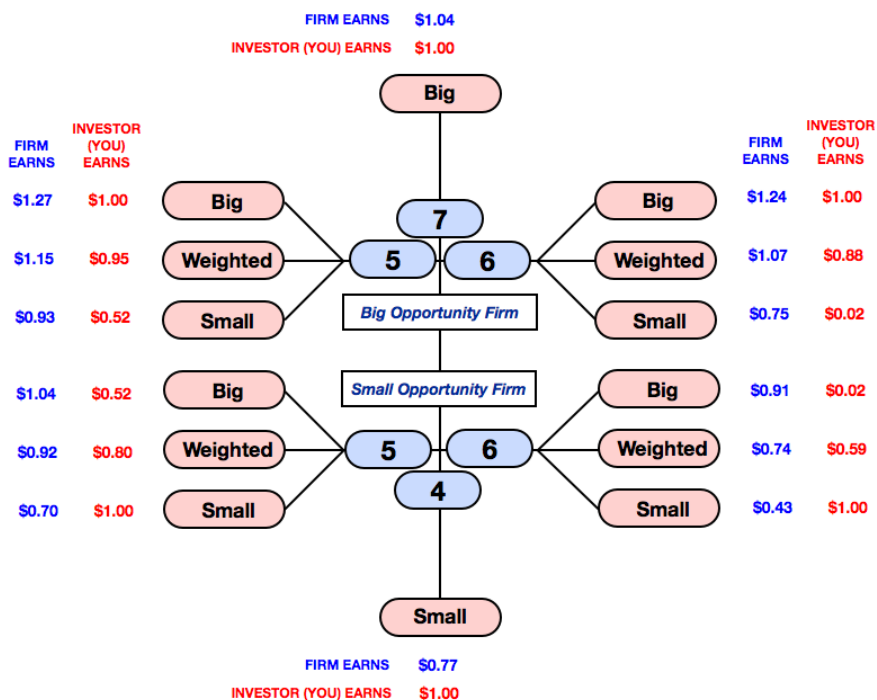
Figure 2 provides the extensive form view of Scenario 2 from the investor’s perspective. Note that the structure of this scenario is similar to that of Scenario 1, although with different payoffs. In this case, the payoffs are determined by increasing the unit price by 6.67% (from 0.75 to 0.80) in the underlying newsvendor model used to generate the player payoffs. Figures 4 and 5 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. Table 2 identifies the outcomes predicted by the Undefeated and Intuitive Criterion refinements in each experimental scenario.

5 Experiment

5.1 Method

Participants. Participants (N=228, Median age=25, 48% female) completed this experiment in a behavioral 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 their decisions. 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.

Figure 2: Extensive form of Scenario 2, with the display formatted for presentation to an investor. There is a 35% probability that the subject in the role of the firm is randomly assigned to be a “Small” opportunity type firm.



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

Subjects considered each of the six scenarios from both the perspectives of a firm and an investor, resulting in a total of 12 rounds. At the beginning of each round, subjects were randomly and anonymously paired with one another and notified of their role for the round (firm or investor).

Next, the matched pair of subjects 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, subjects were asked to anticipate the choices they would make under different realizations of the scenario. Subjects 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, subjects 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 subjects prior to capturing their direct responses during actual game play for two reasons. First, by asking the subjects 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.⁴

Next, based on the stated probability, the software designated the firm to be facing a “Big” or “Small” opportunity, revealing this information only to the subject playing the role of the firm. Upon receiving this private information, the subject 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 scenarios. However, we also wished to facilitate a deep understanding of the game among the subjects. To that end, subjects completed a scenario in one role (firm or investor) and then completed the same scenario in the other role before

⁴A strength of the strategy method is that it may lead subjects 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 subjects 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 subjects fully consider each scenario, but we perform our analyses on direct response data captured during actual game play.

moving on to a new scenario. Finally, we sought to mitigate the effects of retaliation from past rounds by pairing subjects with new, anonymous, and randomly-selected partners at the beginning of each round.

5.2 Measures

Table 3 summarizes the variables used in our analysis, Table 4 provides summary statistics and correlations, and Table 5 summarizes the categorical variables by subject.

5.2.1 Dependent Variables

We utilize three dependent variables in our analysis. We employ two dichotomous variables, *Undeclared* and *Intuitive*, to analyze whether subjects make choices consistent with the Undeclared or Intuitive Criterion refinement. *Undeclared* is set to ‘1’ if the firm’s choice conforms to the Undeclared 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 utilize a continuous variable, *Payoff*, to analyze whether firms make more money when their choice conforms to either refinement. This variable captures the payoff the subject receives in each round regardless of whether this amount is included in the subject’s bonus.

5.2.2 Independent Variables

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.⁵ To analyze whether the subject’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 subject 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

⁵We implemented several features in our experimental design to foster a better understanding of the game among the subjects, including asking subjects to enter their strategies before each round of play, having subjects switch roles and play the game both as a firm and an investor, and playing multiple rounds.

game we just played?” Based on these responses we set *Understanding* to ‘1’ if the subject rated their understanding as a ‘5’ or higher and ‘0’ if they rated it a ‘4’ or lower. We encode subjects 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 subject did not respond and ‘0’ otherwise.

Subjects generally indicated a high level of understanding of the game – 86.3% of subjects 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.

Undeclared and *Intuitive*, as described in Section 5.2.1, serve as the key independent variables in our analysis of whether the firm’s payoff is impacted by making choices which conform to either the Undeclared or Intuitive Criterion refinements.

5.2.3 Control Variables

We collect several 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 subjects that are randomly assigned to have a “Big” opportunity in the current round. *Switch* identifies whether the subject’s final choice deviated from the initial strategy they entered prior to learning their type. *Session* identifies the experimental session in which the subject participated. *Sequence* reflects the order in which a scenario is presented to a subject and captures changes in behavior as subjects see more scenarios.

We also include demographic information on the subjects. *Age* is the age of the subject at the time of the experiment. *Female* identifies the subject’s gender. *Ethnicity* reflects the subject’s self-affiliated ethnicity. *Education* is a categorical variable capturing the most recent level of education attained by the subject. *ESL* reflects whether the subject considers English to be their second language. The categories used for the categorical variables are presented in Table 3.

5.3 Empirical Models

Our primary analyses evaluate (1) the consistency of subjects’ decisions with the predictions of the Intuitive Criterion and Undeclared refinements and (2) whether changing the unit price in the

underlying model impacts subject behavior. We expand our analysis by also evaluating (3) whether the participant’s level of understanding of the game and the complexity of the game influence the predictive power of each refinement and (4) whether behavior consistent with each refinement has an impact on payoffs. We evaluate the first two research questions using two-sided binomial tests. The empirical models we use to analyze the latter two questions are described below.

5.3.1 Impact of *Understanding* on Refinement Predictions

We are interested in the relationship between each subject’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 subjects 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 behavior of decision makers with 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:

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

where subscript i denotes the subject 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 (instruction errors, 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 subjects. Finally, *Female*, *Ethnicity*, and *ESL* control for any differences that may be associated with gender or ethnicity.

5.3.2 Impact of Behavior on Payoffs

To evaluate whether subjects who make choices that are consistent with the Undefeated refinement or the Intuitive Criterion refinement earn a higher payoff, we estimate the following OLS

specification, which we estimate with robust standard errors clustered by participant:

$$\begin{aligned}
 \text{Payoff}_{ij} = & \gamma_0 + \gamma_1 \cdot \text{Undeatead}_{ij} + \gamma_2 \cdot \text{Intuitive}_{ij} + \gamma_3 \cdot \text{Understanding}_i + \\
 & \gamma_4 \cdot \text{Understanding - No Response}_i + \gamma_5 \cdot \text{Big}_{ij} + \gamma_6 \cdot \text{Switch}_{ij} + \\
 & \xi' X_i + \epsilon_{ij}.
 \end{aligned} \tag{3}$$

where *Payoff* is the payoff for the subject in each round. The other variables and vector of controls are as described for Equation (2). By comparing the payoffs earned by firms exhibiting behavior 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 behavior associated with one refinement methodology is more profitable in our experimental market than behavior consistent with the other, we would assert that an actual firm, helmed by actual decision makers, may have incentives to exhibit such behavior in practice.

6 Results

6.1 Predictive Power of Intuitive Criterion and Undeatead Refinements

Table 6 presents the degree to which subjects' decisions conformed to the predictions of the Undeatead and Intuitive Criterion refinements in each experimental scenario. In our experiment, the majority of subjects' decisions followed the predictions of the Undeatead refinement. Its predictive power across scenarios ranged from a low of 55.7% accuracy for Scenario 4 to a high of 71.1% accuracy for both Scenarios 1 and 5. Subjects' 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.

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 subjects' 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. Subjects' decisions conformed to the predictions of the Undeatead 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 Undeclared refinement, which predicted 63.5% of subjects' decisions ($p < 0.001$; two-sided), relative to an expectation of 33.3% if it instead had no predictive power.⁶

In contrast, subjects' decisions were not predicted by the Intuitive Criterion refinement. In five of the six scenarios, subjects made choices which conformed with the Intuitive Criterion refinement *less often* than what would be expected if subjects 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 subject responses conformed to 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 subjects' decisions ($p < 0.001$ two-sided), has less predictive power than an expectation of 33.3% if subject choices were purely random.⁷

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 subjects made decisions that were not predicted by either refinement, leaving 1,156 observations. If neither refinement were predictive, then we would expect to see subjects splitting their decisions evenly between the options. However, 869 of 1,156 choices (75.2%) conformed to the Undeclared refinement, while the remaining 287 choices (24.8%) conformed to 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).

6.2 Sensitivity to Newsvendor Unit Price

As described in Section 4, 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

⁶As a robustness test, we also considered just the first scenario seen by each subject. Since scenarios are randomly assigned, different scenarios will be presented first to different subjects. We find strong support for the predictive power of the Undeclared refinement, which predicted 56.1% of subjects' decisions ($p < 0.001$; two-sided), relative to an expectation of 33.3%.

⁷We again considered just the first scenario seen by each subject and find that firms made choices which conformed with the Intuitive Criterion refinement 24.6% of the time ($p < 0.01$ two-sided), far less often than what would be expected if subjects were simply making random selections.

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 subject behavior differs across these scenario pairs. Rows 2 and 4 of Table 6 summarize these results.

As shown in Table 6, conformance with the Undefeated refinement is higher in Scenarios 1, 3, and 5 than in Scenarios 2, 4 and 6. The difference in the proportion of subjects whose behavior conforms with the Undefeated 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 subjects whose behavior 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 is negative and statistically significant (diff = -0.086, $p < 0.001$ two-sided).

To understand these results, recall from Section 3.2 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, subjects 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).⁸ 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

⁸The 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).

PBE in Scenario 1 (\$0.63 versus \$0.52) and a 19% higher payoff in Scenario 2 (\$0.92 versus \$0.77).⁹

Using this rationale, we expect to see a smaller proportion of “Big” opportunity firms comply with the Undeclared refinement in Scenario 2 compared to Scenario 1, and approximately the same proportion of “Small” opportunity firms. As summarized in Table 7, our results confirm this intuition. The proportion of “Big” opportunity firms exhibiting behavior that complies with the Undeclared 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 exhibiting behavior that complies with the Undeclared refinement is 0.9 percentage points lower in Scenario 2 compared to Scenario 1 ($p = 0.90$ two-sided). Table 7 shows similar results comparing Scenario 3 to Scenario 4 and Scenario 5 to Scenario 6.

These findings support the underlying logic behind the Undeclared 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 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 is an important as it highlights that model parameters can influence whether subjects conform to different refinement theories beyond simply determining whether an equilibrium outcome exists and survives a particular refinement.¹⁰

6.3 Impact of *Understanding* on Refinement Predictions

Table 8 presents the results of our estimation of Equation 2, which tests whether the subject’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 Undeclared refinement’s predictions and Model (2) tests for

⁹There 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).

¹⁰It 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.

consistency with the Intuitive Criterion refinement’s predictions. As shown in Model (1) of Table 8, subjects reporting a high level of understanding of the game were more likely to make choices consistent with the Undeclared refinement than subjects 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 Undeclared refinement for subjects with a high self-reported understanding of the game ($Understanding = “1”$) versus 0.51 for subjects with a low self-reported understanding of the game ($Understanding = “0”$).¹¹ From Model (2), subjects reporting a high level of understanding of the game were less likely to make choices consistent with the Intuitive Criterion refinement than subjects reporting a low level of understanding of the game (coeff -0.91, $p < 0.001$, OR = 0.40). This effect corresponds to a 0.19 predicted probability of making a choice consistent with the Intuitive Criterion refinement for subjects with a high self-reported understanding of the game ($Understanding = “1”$) versus 0.35 for subjects with a low self-reported understanding of the game ($Understanding = “0”$). 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 subjects with a higher understanding of the game were more likely to make choices predicted by the Undeclared refinement than by the Intuitive Criterion refinement.¹²

6.4 Impact of Behavior on Payoffs

Table 9 presents the OLS estimation of Equation 3 specifying the relationship between the subjects’ payoffs and whether their choices were consistent with either the Intuitive Criterion or Undeclared refinements. Model (1) includes both *Undeclared* 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 subject. In model (1), the coefficient on *Undeclared* 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 subjects who make choices that are predicted by the Undeclared 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

¹¹This is the average marginal effect (AME) of $Understanding$ over all observations.

¹²As a robustness check, we consider more granular categorizations to measure subject understanding and all of our inferences remain the same.

in the payoff earned by subjects 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.

Model (2) shows that subjects who made choices that were predicted by the Undefeated refinement earned a higher payoff (coeff 0.07, SE 0.01, $p < 0.001$), earning on average \$0.07 more in each round than subjects who made alternative choices. This corresponds to an average 8.4% increase in the payoff earned by subjects when their choice is consistent with the Undefeated refinement. Finally, Model (3) dichotomizes the subjects' choices into those that are predicted by the Intuitive Criterion and those that are not, and shows that subjects who made choices that were predicted by the Intuitive Criterion refinement earned a lower payoff than those who made alternative choices (coeff -0.08, SE 0.01, $p < 0.001$). This corresponds to an average 9.1% decrease in the payoff earned by subjects when their choice is consistent with the Intuitive Criterion refinement.

7 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 settings relevant to operations management. Existing research has focused on the least cost separating PBE outcomes, either by assumption or as a result of applying the Intuitive Criterion refinement. In this section, we consider how the results of such research can be extended by considering pooling PBE which may exist and survive the Undefeated refinement. As an example, we examine the implications for Cachon and Lariviere (2001), the most widely cited signaling game paper in the operations management literature.

7.1 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. There are two compliance regimes in the paper. In the forced compliance regime the supplier is obligated to build the capacity level dictated by the manufacturer. In this case, the high type manufacturer can signal for free and retains all of the supply chain profits. We focus our discussion on the voluntary compliance regime 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.

Cachon and Lariviere focus 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, the authors “defer the analysis of pooling equilibria to future research.” We apply the Undefeated refinement to highlight how the analysis in this paper can be extended to include pooling equilibria, as envisioned by the authors. Using the Undefeated refinement provides three incremental 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 enables an analysis of the behavior of the players under these different equilibrium outcomes.

We adopt the authors’ notation and summarize important aspects of the model here, though the reader should refer to Cachon and Lariviere (2001) 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, Cachon and Lariviere (2001) use w_θ in place of w_e to reflect different wholesale prices offered by the two manufacturer types, where $w_\theta(K) = \frac{cK}{F_\theta} + c_p$.

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.

7.2 Allowing for Pooling PBE

We generalize these results to account for a pooling PBE that survives the Undeafated refinement. In many cases, there will exist multiple pooling PBE that provide both types of manufacturer a higher payoff than is realized under the separating PBE. For ease of exposition, 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 manufacturer wishes to be perceived as a high type manufacturer rather than the opposite.

We utilize some additional notation to present these results. Let λ denote the posterior probability that the manufacturer is a high type and $1 - \lambda$ denote the posterior probability that she is a low type. Let $F_P = \lambda F_H + (1 - \lambda)F_L$ 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 $\lambda = \rho$ 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.,

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

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:

$$\Pi_\theta(K, \lambda) = (r - w_\lambda(K)) S_\theta(K), \quad (7)$$

where $w_\lambda(K) = \frac{cK}{F_P} + c_p$. Note that when $\lambda = 1$, we recover Equation (4) for $\tau = H$, and when $\lambda = 0$ 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_λ , provided $\Pi_H(K, \lambda) > \max_{K, m, a} \Pi_H(K, m, A)$ and $\Pi_L(K, \lambda) > \Pi_L(K_L^*, L)$. These conditions are also sufficient for the pooling PBE at K^P to survive the Undefeated 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.

7.3 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 Undefeated 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 3a 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 3b introduces the expected profit curves for both manufacturer types under a pooling PBE using Equation (7) for $\lambda = \rho$. 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

In our example we assumed $\rho = 0.10$, 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 $\rho \in (0, 0.25)$.

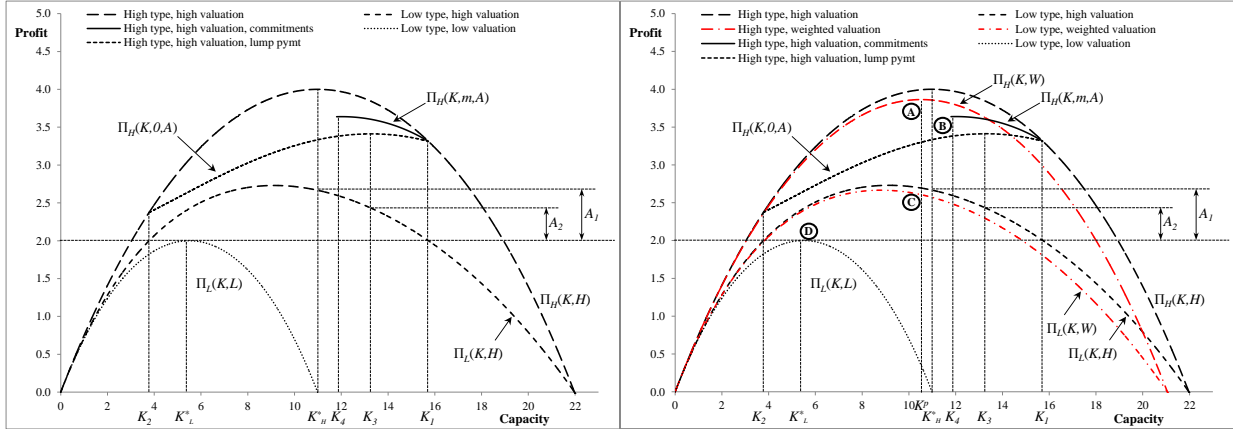
7.4 Applications to Other Research

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, Lai et al. 2012), franchising decisions (Desai and Srinivasan 1995), channel stuffing (Lai et al. 2011), and market encroachment by suppliers (Li et al. 2013). The outcome examined in each of these papers is the least cost separating

Figure 3: Manufacturer's Profit as a Function of Capacity with Exponential Demand Under Voluntary Compliance.

(a) Results exclude the possibility of a pooling PBE.

(b) Results include the possibility of a pooling PBE with $\rho = 0.10$.



PBE. In each case, however, a pooling PBE exists and survives the Undeafated refinement across some set of model parameters. We leave a detailed analysis of the implications of applying the Undeafated refinement in these settings to future research.

8 Implications and Conclusions

While decision making under information asymmetry is a burgeoning field within operations management, little has been done to reconcile the behavior of actual decision makers with the assumptions that underlie models in this area. 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 behaviors, which are not regularly considered in the extant theory, were widespread among subjects, relative to separating behaviors. In particular, averaged across all scenarios, subject behavior was more than three times more likely to conform with the Undeafated refinement than the Intuitive Criterion refinement, which 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 behavior 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 behavior in our experiment, which suggests that subjects 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. We observe that subjects who report a high level of understanding of the game are significantly more likely to exhibit behaviors that are consistent with the Undefeated refinement than subjects who report a low level of understanding. Third, we expect managers to use strategies that generate higher payoffs. In our experiment, subjects who exhibited behavior that was consistent with the Undefeated refinement earned higher payoffs from investors on average than subjects who exhibited behavior consistent with the Intuitive Criterion refinement. This is particularly interesting in the context of our experiment, in which subjects 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 will increasingly gravitate toward the strategy that returns the highest payoff. Indeed, in our experiment, while subject behavior overwhelmingly conformed with the predictions of the Undefeated refinement, even during the first rounds of game play, the tendency to exhibit such behavior intensified as subjects 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 subjects learning the efficacy of various strategies and converging on the most successful one over time. All of these patterns observed among the subjects in our experiment are consistent with the behavior 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 providing 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. Hence, we expect this growing area of operations management research to continue to flourish. To the extent our results expand the set of anticipated managerial behaviors in these contexts, exploring their operational implications through the application of the Undeclared refinement may enrich the extant theory. Opportunities may exist to revisit established models, as well as explore the implications of these behaviors in new settings. Empirical research that explores these behaviors and their implications in practice is another promising future direction that we leave 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	r	s	c	α	g	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 Undefeated refinement and Intuitive Criterion refinement predictions for each scenario.

	Scenario:					
	1	2	3	4	5	6
Undefeated	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: Description of Variables

Variable	Description
<i>Undefeated</i>	Indicator variable identifying whether the Undefeated 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 subject received in the round
<i>Understanding</i>	Indicator variable identifying whether the subject 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 subject rated their understanding ('1') or not ('0')
<i>Big</i>	Indicator variable identifying whether the subject is a Big type in current round ('1') or a Small type ('0')
<i>Switch</i>	Indicator variable identifying whether the subject'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 subject
<i>Age</i>	Subject's age
<i>Female</i>	Indicator variable identifying whether the subject is female ('1') or male ('0')
<i>Ethnicity</i>	Categorical variable indicating whether the subject is African-American, Asian, Caucasian, Hispanic, Pacific Islander, or Other
<i>Education</i>	Categorical variable indicating whether the subject has a high school diploma, some college, a bachelors degree, or an advanced degree
<i>ESL</i>	Indicator variable identifying whether English is subject's second language ('1') or primary language ('0')

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

Table 4: 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 5: Distribution of subjects for categorical variables

Education Level	Frequency	Percent
High School	21	9.21
Some College	114	50.00
Bachelors	48	21.05
Masters	31	13.60
Doctorate / Professional	10	4.39
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
Pacific Islander	18	7.89
Other / Missing	6	2.63
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 6: The proportion of subject decisions predicted by the Undefeated and Intuitive Criterion refinements.

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

Notes: The percentages in row 1 identify the proportion of subjects whose choices conform to the Undefeated 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 subjects 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 7: The proportion of subject decisions which comply to the Undeafated refinement, differentiated by firm type.

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

Dependent Variable:	(1)		(2)	
	<i>Undeafated</i>	OR	<i>Intuitive</i>	OR
<i>Understanding</i>	0.68*	1.97*	-0.91***	0.40***
	[0.28]	[0.56]	[0.27]	[0.11]
<i>Understanding - No Response</i>	-0.50	0.61	-1.61+	0.20+
	[0.94]	[0.57]	[0.94]	[0.19]
<i>Big</i>	-0.93***	0.39***	0.42*	1.52*
	[0.17]	[0.07]	[0.19]	[0.29]
<i>Switch</i>	-0.83***	0.44***	0.44+	1.56+
	[0.22]	[0.10]	[0.23]	[0.36]
Constant	1.01*	2.74*	-1.25*	0.29*
	[0.48]	[1.33]	[0.51]	[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 subject 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 subject’s payoff depends on their choice being predicted by the Undeclared refinement or the Intuitive Criterion refinement.

		Dependent Variable: <i>Payoff</i>		
		(1)	(2)	(3)
(A)	<i>Undeclared</i>	0.04** [0.01]	0.07*** [0.01]	
(B)	<i>Intuitive</i>	-0.05*** [0.01]		-0.08*** [0.01]
	<i>Understanding</i>	0.01 [0.01]	0.02+ [0.01]	0.01 [0.01]
	<i>Understanding - No Response</i>	-0.02 [0.03]	-0.00 [0.03]	-0.03 [0.03]
	<i>Big</i>	0.23*** [0.01]	0.23*** [0.01]	0.22*** [0.01]
	<i>Switch</i>	0.02 [0.01]	0.02 [0.01]	0.01 [0.01]
	Constant	0.62*** [0.02]	0.59*** [0.02]	0.66*** [0.02]
	Observations	1,368	1,368	1,368
	R^2	0.38	0.37	0.37
	Mean DV	0.85	0.85	0.85
	Wald F : (A)-(B)=0?	67.37***		

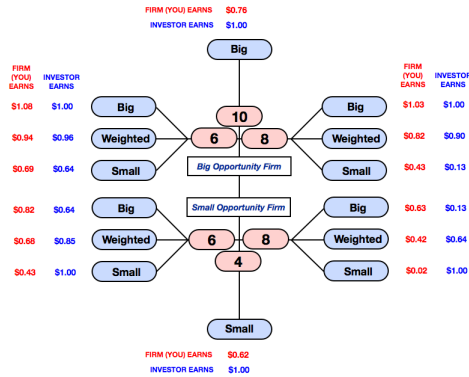
Notes: OLS estimation with robust standard errors clustered by subject in brackets. Included controls – *Session*, *Wait*, *Age*, *Female*, *Ethnicity*, *Education*, *Student*, and *ESL*. Wald tests of indistinguishable coefficients report F statistics. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, +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

Appendix

Extensive Form Representations

Figure 4: Extensive form of Scenarios 3 and 4.

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



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

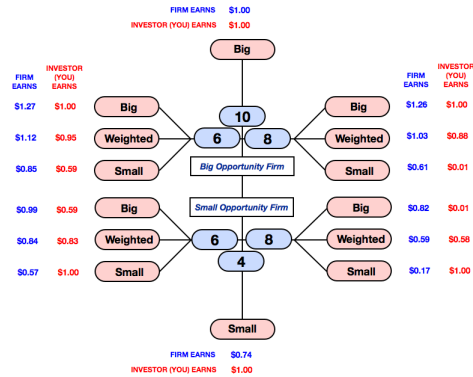
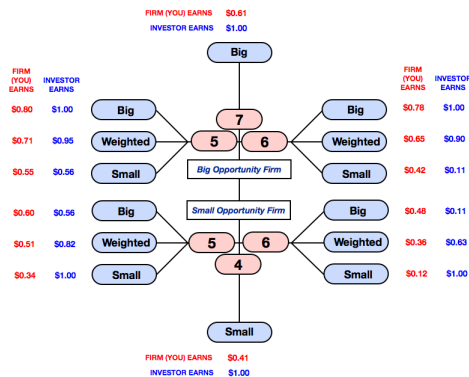
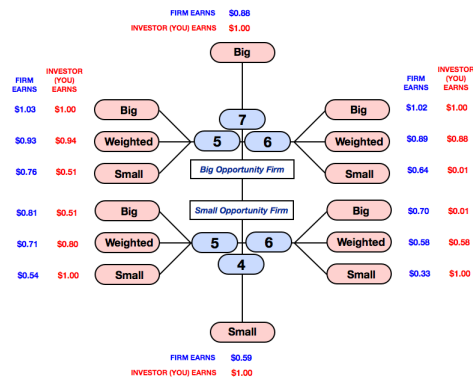


Figure 5: Extensive form of Scenarios 5 and 6.

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



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



Subject Instructions Script

The script read to all subjects in the experiment is below. A copy of the presentation slides that accompany the script is available upon request from the authors.

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 simply 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 either \$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 either \$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 potentially 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.