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Money Isn’t Everything: Estimating the Prestige Value of Winning Cutthroat Kitchen from Overbidding in Sabotage Auctions
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ABSTRACT

We seek to estimate the prestige value of winning beyond monetary prizes in Cutthroat Kitchen, a cooking show in which dishes are judged in a series of elimination rounds, with the twist that action is periodically paused to auction sabotages against rivals. We estimate the distribution of contestants’ prestige values using a structural model of bidding by a contestant with rational expectations about sabotage effectiveness taken from the data. Our most conservative specification—allowing for risk aversion and bias in the beliefs about sabotage effectiveness—yields mean prestige values of nearly$10,000 for typical episodes and over $35,000 for tournaments.

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1. Introduction

The literatures in sociology and economics have long recognized (see, e.g., Veblen, 1899; Keasbey, 1903) that individuals are motivated not only by money (and the consumption it buys) but also by the less quantifiable concept of social status, henceforth referred to as prestige. In this paper we seek to quantify individuals' tradeoff between money and prestige using data from the cable-television show *Cutthroat Kitchen*, a cooking competition aired in the United States by the Food Network from 2013 to 2017, a top-ten ranked cable show at the height of its run.[1] In the show, contestants prepare dishes that are judged in a series of elimination rounds, with the added twist that action is periodically paused to auction sabotages that impair rivals' cooking. Contestants bid for sabotages out of a $25,000 initial stake. The contestant who survives elimination at the end of the episode is the winner, taking home any money from the initial stake that has not been spent on sabotages as prize money, while the others win nothing. The winner also gains the prestige of winning a television show, reflecting among other things the contestant's cooking skill and savvy.

For this study, we hand collected data for a complete set of *Cutthroat Kitchen* episodes. *Cutthroat Kitchen* provides an opportune setting to study the tradeoff between prize money and prestige because of the sabotage auctions embedded in the show. The English format of the sabotage auction allows researchers to observe the sequence of contestants' bids, revealing information about their values of winning the episode. If a contestant's value of winning exceeds his or her stake, which constitutes his or her potential monetary prize, we can infer that the contestant's residual prestige value is positive.

A numerical example will help illustrate the inference process. For simplicity, consider the last sabotage auction in the last round of the episode, when only two contestants remain. Suppose a risk-neutral contestant A, exhibiting no behavioral biases, having $10,000 left over after bidding in previous auctions, bids for a last sabotage that will reduce A's chance of winning by 20% if his or

[1] *Cutthroat Kitchen* was ranked tenth in the 18–49 age group according to Neilsen ratings for original cable shows aired on May 24, 2015 (Metcalf, 2015).

her rival obtains it instead of A. If A only values prize money, he or she should be willing to bid no more than \$2,000. Any higher bid would reduce A's prize money conditional on winning by a greater percentage than obtaining the sabotage increases A's probability of winning, reducing A's expected prize money. If A bids more than \$2,000, it can be inferred that he or she obtains prestige value above and beyond the prize money.

In order not just to demonstrate the presence of prestige value but to quantify it, we construct a structural model of the last sabotage auction in which winning an episode provides the contestant with utility from prize money and an additive prestige factor. Contestants have rational expectations about the effect of sabotaging the remaining rival consistent with empirical probabilities of winning with or without sabotages observed in the data. A contestant's bid in a sabotage auction provides a lower bound on his or her willingness to pay for the increase in the probability of winning the episode from obtaining the sabotage. In those cases in which a rival outbids the contestant for the sabotage, the rival's bid provides an upper bound on the contestant's willingness to pay (unless the contestant is liquidity constrained). These bounds on a contestant's willingness to pay can be translated into bounds on his or her prestige value. Assuming a functional form for the distribution of prestige values—we use the normal distribution—the parameters of the prestige-value distribution—mean and standard deviation—can be estimated by maximizing the likelihood the prestige values fall into the observed bounds.

The simple model of risk-neutral contestants with rational expectations about sabotage effectiveness omits two important alternative factors aside from prestige value that could explain overbidding in the sabotage auctions. One important factor is risk aversion. As is well known since Harris and Raviv (1981), risk aversion can lead buyers to raise their bids, seeking insurance against the untoward outcome of losing the object for which they pay a risk premium in the form of a higher bid. That result, however, applies to sealed-bid, first-price auctions, not English auctions, in which buyers' bids for an indivisible object are unaffected by risk aversion, equaling their private values in any event (Harris and Raviv, 1981). In our setting, in which the auctioned sabotage does not guarantee the desired end—victory in the episode—but is just a lottery with improved odds of victory, risk aversion has the direct effect of increasing a bidder's private value for the better lottery, increasing their equilibrium bids even in an English auction.[2] We accommodate risk aversion by specifying a constant absolute risk aversion (CARA) utility function in the structural model and estimating the CARA coefficient as a parameter.

Another important factor that could inflate bids is bias in beliefs about sabotages, in particular in the direction of overestimating how much they impair rivals' cooking. Without further discipline, any amount of overbidding can be explained with sufficiently biased beliefs. Our setting provides a compelling justification for overestimating the effectiveness of the last sabotage. Our empirical estimates show that the last sabotage in the last round is significantly less effective on average than earlier sabotages in that round. Contestants who base their beliefs on the data but are inattentive (as in Schwartzstein's 2014 theory of selective attention) to sabotage order would be biased in the direction of overestimating the value of the last sabotage. To gauge the importance of bias in beliefs, we estimate a version of the structural model with inattentive beliefs to sabotage order and compare the estimates to the baseline with fully attentive beliefs.

Accounting for risk aversion and biased beliefs cuts our estimates of mean prestige values about in half. Still, estimates of mean prestige values remain high. For standard episodes, mean prestige is an estimated \$9,600, close to the \$11,000 mean monetary prize for episode winners. The mean prestige value is \$35,100 for finales of multi-episode tournaments, significantly higher than standard episodes, consistent our priors that tournaments are especially prestigious. The prestige value of tournament finales eclipses the prize money won in them. We find little evidence that prestige value is correlated with demographics like race or gender. Contestants who come in with prestigious job titles like chef or restaurant owner gain significantly less prestige value from winning (by \$6,000 or more) than others whose rise in the profession may be aided by winning a widely viewed cooking

[2]The literature on auctioning lotteries to risk-averse bidders is scant (Vasserman and Watt, 2021). One recent exception is Baisa (2017), who shows how standard auctions in the presence of risk-averse bidders can be improved by integrating lotteries into auction design.

competition.

While we have accounted for some of most important additional factors that could contribute to overbidding; it is impossible to anticipate the full range of factors, and even factors that can be anticipated may be difficult to control for. The literature on behavior biases in auctions suggests that the open-outcry, ascending-bid format used in *Cutthroat Kitchen* auctions is particularly susceptible to a number of behavioral biases that contribute to what might be called “bidding fever.” Bidding fever might stem from an endowment effect, whereby bidders develop an attachment to the object through the course of bidding may lead them to bid more than their initial value (Heyman, Orhun, and Ariely, 2004; Ehrhart, Marion, and Abele, 2015; Offerman, Romagnoli, and Ziegler, 2022), or it might stem from growing spite toward opponents contending for the object (Andreoni, Che, and Kim, 2007; Bartling, Gesche, and Netzer, 2017; Offerman, Romagnoli, and Ziegler, 2022).

The auction studies cited in the previous paragraph are all laboratory experiments, which can identify behavioral biases by cleverly controlling auction conditions. Our observational data do not afford such tight controls. Yet some nuances in our results bolster confidence that we have identified prestige values from other explanations of overbidding. Mean prestige values are not constant across episode types but are higher for the types we expect should generate more prestige. This correlation that is not an obvious implication of endowment effects, spite, or other factors besides prestige values. Furthermore, mean prestige values are also correlated with the prestige of contestants’ job titles. This correlation is consistent with the story that contestants bid the most who have the most prestige to gain and less obviously related to endowment effects or spite. Finally, in a number of observations, contestants bid away all or virtually all of their potential prize money. Such behavior would appear too extreme to explain as an endowment effect or spite without an intrisic value of winning beyond prize money. Certain aspects of our game-show setting may weaken behavioral biases behind bidding fever apart from prestige. Bidding fever eventually hits a hard cap provided by the constraint that bids are paid out of remaining stakes, potentially dampening the fever as the cap is approached. The winning bidder obtains not an object to keep but temporary use of a sabotage for the duration of the round. The prospect of temporary usage may generate a weaker endowment effects than permanent ownership.

Our paper is organized as follows. Section 2 outlines our contribution to related literatures. Section 3 provides background on the *Cutthroat Kitchen* show. Section 4 details our data-collection efforts and provides descriptive statistics for the sample of episodes. Section 5 lays out the structural model of the last auction in an episode. Section 6 describes our empirical methodology. Section 7 reports our estimation results. First, we report the effect of sabotages on the probability of winning, estimated using a linear probability model. With these estimates in hand as inputs into bounds on willingness to pay, we proceed to estimate the mean and standard deviation of the distribution of prestige values using maximum likelihood. Section 8 concludes.

2. Related Literature

Our paper is perhaps closest to the economics literature measuring an individual's intrinsic prestige value from his or her employment or other activities. Focke, Maug, and Neissen-Ruenzi (2017) find that CEOs who work for prestigious firms experience a compensating differential, earning less than peers. Kleinjans, Krassel, and Dukes (2017) suggest that the prestige associated with working in socially conscious occupations can explain a portion of the gender wage gap. Zhan (2015) links heterogeneity in workers' tradeoffs between salary and prestige to norms in racial, ethnic, and neighborhood groups. Harbaugh (1998) analyzes the prestige value of charitable giving when it is publicly reported using observational data on law-school donations. Li and Riyanto (2022) provides a related field experiment, and Ariely, Bracha, and Meier (2009) provides a related laboratory experiment. Pascual-Ezamam, Prelec, and Dunfield (2013) studies whether dishonest behavior can be motivated by prestige in the laboratory. Harbaugh (1998) provides a theoretical analysis.

A series of papers seeks to estimate the market return from awards, ranging from the 5.4% additional premium buyers pay for houses designed by award-winning architects (Liao, Jing, and

Lee, 2022), the \$500,000 additional revenue earned by movies starring an Oscar or Golden Globe winner (Elberse, 2007), or the 12% boost in attendance at a Broadway production when one of the actors wins a Tony award (Boyle and Chiou, 2009). As the survey by Frey and Gallus (2017) notes, causally identifying the economic returns from awards is difficult in cross-sectional studies because the award winner's skill may be an omitted variable that drives the association between award and revenue. The better studies in this literature leverage panel data, measuring the bump in revenue timed with the award's announcement. Our paper seeks to estimate the intrinsic value to the award winner themselves. Of course, this intrinsic value may be due in no small part to the market signal it sends, for example, leading future employers to offer the winner a higher wage.[3]

A broader literature measures the value of reputation gained through means other than awards. Teubner et al. (2016) studies the effect of an increase in host ratings on revenue earned from Airbnb rentals. Manabe and Nakagawa (2022) quantify the greater stock crash during the Covid-19 pandemic suffered by firms with lower reputation for product usefulness. Pfeiffer et al. (2012) design a laboratory experiment in which a reputation for being cooperative in the Prisoners Dilemma can be traded. Gunter (2014) provides a general discussion of the value of celebrity.

Our paper is part of the literature measuring economic variables using data from game shows, exploiting the advantages of a stylized setting with well-defined rules as in a laboratory experiment but offering much higher stakes than research budgets can afford. Many game-show studies focus on estimating risk preferences, including the study of *Card Sharks* by Gertner (1993), *Jeopardy* by Metrick (1995), *LINGO* by Beetsma and Schotman (2001), *Hoosier Millionaire* by Fullenkamp, Tenorio, and Battalio (2003), and *Deal or No Deal* by Post et al. (2008). We also estimate risk preferences in our structural model, they are only of secondary interest in our paper, included to provide cleaner estimates of the distribution of prestige values, which is our central focus. In contrast to Gertner (1993) and Beetsma and Schotman (2001) but consistent with Metrick (1995) (as well

[3] A non-technical but comprehensive discussion of cultural awards and their associated prestige is provided in the book English (2008) (which ironically received the *New York Magazine* award for Best Academic Book in its publication year).

as Fullenkamp, Tenorio, and Battalio (2003) at least for moderate gambles), contestants do not exhibit much risk aversion in our game show. Buser, van den Assem, and van Dolder (2023) study contestants' aversion to competition in a Dutch version of *Deal or No Deal*, finding that women are averse to competing against men. We find little evidence of gender differences, but this is not a direct contradiction of Buser, van den Assem, and van Dolder (2023) since we study a different variable, prestige rather than competitiveness. Oran and Yurtkoru (2019) also find few gender differences in their analysis of bidding behavior in auctions arising in the Turkish game show *I Don't Know, My Spouse Knows*. To our knowledge, we are the first paper to study the prestige value of winning a game show and the first to study *Cutthroat Kitchen*.

Our paper is related to the large literature on bidding behavior in auctions given that we use bids in sabotage auctions to identify prestige values. The auction literature is too vast to survey here. The most closely related papers link overbidding to various behavioral biases that might generate "bidding fever," whether an endowment effect (Heyman, Orhun, and Ariely, 2004; Ehrhart, Marion, and Abele, 2015), spite toward opponents (Andreoni, Che, and Kim, 2007; Bartling, Gesche, and Netzer, 2017), or both (Offerman, Romagnoli, and Ziegler, 2022). Since we incorporate risk aversion in our bidding model and estimate a CARA coefficient, our paper is related to the theoretical and empirical literature on risk aversion in auctions, surveyed in Vasserman and Watt (2021). As noted in the introduction, the connection is subtle. Harris and Raviv (1981) showed that risk aversion is immaterial for bids in the auction format used in *Cutthroat Kitchen*—single-unit, ascending-bid auctions—only mattering for other formats such as first-price sealed-bid auctions (in which higher risk aversion induces bidders to submit higher bids). While the sabotage auctions we study are single-unit, ascending-bid auctions, the winning bidder does not keep the unit but employs it to increase the chance of winning. In effect, what is auctioned is a higher probability of winning the episode. The more risk-averse are bidders, the more they are willing to pay for an increase in probability of winning. In this respect, our paper is related to Baisa (2017), who studies optimal auctions of lotteries over objects in the presence of risk-averse bidders.

3. Background on *Cutthroat Kitchen*

Cutthroat Kitchen is a reality-television style cooking competition that aired on Food Network cable channel in the United States from 2013 to 2017, hosted by the television personality and gourmet, Alton Brown. Each episode has three rounds. In each round, competitors prepare a dish which is judged by a guest expert at the end of the round in a blind taste test. The contestant with the worst dish is eliminated. At the end of three rounds, the field of four initial contestants is winnowed down to a single episode winner. Contestants are typically professional cooks ranging from line cooks to private chefs, to executive chefs. Others are restaurant owners or in some cases amateur cooks.

In each round, contestants are told to make a specified dish, whether it be pizza, gumbo, or baklava. They are given a small amount of time during which they scramble in a pantry to gather ingredients they will use to cook with. Then the clock restarts and gives then 20 minutes cooking time to complete their dish.

The key difference between *Cutthroat Kitchen* and other televised cooking competitions is that the host pauses the action several times a round to have contestants bid in an auction for a sabotage that can be inflicted on competitors. The sabotages might waste the sabotaged competitor's time (for example, sitting in a corner for a minute while competitors continue cooking), use an inferior tool (for example, cook with a bunsen burner instead of a stove), or use a poor substitute for a key ingredient (for example, ketchup for pizza sauce). The highest bidder gets to choose the competitor on whom to inflict the sabotage (although occasionally sabotages can be applied to more than one competitor).

The show stakes competitors with an initial $25,000. The highest bidder in the auction pays for the sabotage out of his or her stake. The winner of the entire episode receives a monetary prize equal to whatever money is left out of the initial $25,000 that has not been spent in sabotage auctions throughout the game. With three rounds and several sabotage auctions per round, on average, winners end up exhausting a majority of their stake on sabotages. Winners end up with an average monetary prize of about $11,000 in our data, although the lowest prize was a mere $600. Episode losers forfeit their remaining stakes, so it is only the sole episode winner who obtains any money.

In addition to the cash prize, winning *Cutthroat Kitchen* may carry considerable prestige value. Most people will never appear in a television competition, let alone win one. Winning a reality television show undoubtedly provides a "warm glow" to the contestant. For a professional cook, winning a cooking show can burnish his or her reputation. This may lead to long-run monetary benefits beyond the show's prize money, perhaps in the form of higher future salaries.

4. Data

We derived a census of *Cutthroat Kitchen* episodes by consulting the Internet Movie Database (IMDb), an authoritative source of information on movies and television. We validated the comprehensiveness of this census by cross-checking against TV Guide and the Food Network websites. IMDb lists 188 episodes aired between 2013 and 2017, divided into 15 seasons. The sources reported some stray episodes aired in 2019, but these appear to be an Australian version with a different host, which we omit from our data.

Since the show is no longer running, our research team had to rely on streaming services to view and collect data from recorded episodes. Hulu carried most of the episodes, and most of the episodes missing from Hulu were carried on Google Play or Amazon Prime. Only two episodes could not be found on these or any streaming service, and so we had to omit these for lack of data.

Our research team collected detailed data from each available episode. From an initial interview segment, they collected basic demographic information on contestants including gender, race, and status in the cooking profession—whether an amateur, restaurant owner, line cook, or chef, and if the latter, whether a private, sous, executive or other kind of chef. For each of the three rounds, research assistants collected information from all sabotage auctions including the type of sabotage, all contestants' bids in sequence, and the winning bidder. This information allows us to track contestants' remaining stakes at any point in the game and determine the prize for winning the episode. The research assistants recorded which contestant lost each round. Our research team viewed all episodes a second time to double check all data entries for accuracy.

Our research design focuses on the last sabotage auction in the final round. One advantage of this focus on the endgame is that it allows us to abstract from complex dynamic strategies arising in earlier auctions. The general analysis of settings like ours involving auctions among bidders having multiunit demands with synergies across units has proved to be intractable (Kwasnica and Sherstyuk, 2013). Another advantage is that, with only two remaining contestants, we can abstract from more complex strategic interactions arising when three or more players duel (Kilgour, 1973). A final advantage is that the last round happened to be more structured than earlier rounds. Instead of a highly variable number of sabotages, ranging from a low of one to a high of four in earlier rounds, the last round involved two sabotages in the large majority of cases. We dropped the sole episode that had more than two sabotages in the last round. We doubt this one exceptional case led participants to doubt that the second sabotage was the last. In 18 episodes, only one sabotage was auctioned in the last round. We could not rule out that bidders anticipated a further sabotage and adjusted their strategies accordingly, so we drop those episodes from the data. Nine remaining episodes had other idiosyncracies that led us to drop them.[4]

Table 1 provides descriptive statistics for the final sample of 158 episodes used in our analysis, with special emphasis on variables recorded for the last sabotage auction and the 316 remaining contestants that bid in those auctions. Most (80%) of the episodes were stand alone, but *Cutthroat Kitchen* did run some tournaments spanning several episodes. Typically these would involve four preliminary contests, each in its own episode, with the four winners competing in a finale episode. Hence there were four prelims for every finale (the proportionality looks slightly off in the table due to rounding.) The average episode involved about seven sabotage auctions.

[4]We dropped four episodes that started with three rather than the usual four contestants. These lacked a third round since a winner was selected after two rounds. We dropped two episodes in which two teams of two competed instead of four independent contestants. We dropped two episodes that ended in a tie. We dropped one episode that began with a reverse auction that increased rather than reduced contestants' initial stakes.

About two-thirds of contestants were male, about two thirds were white, and about two thirds were some sort of chef. Seven percent were restaurant owners.

The average contestant entered the last auction with a \$13,900 stake. The highest winning bid was \$5,000 on average and the highest losing bid was \$3,700. The average winner walked away with about \$11,000 in prize money.

5. Model

Our model restricts attention to the last sabotage auction in an episode, when just two contestants remain and incentives to influence bidding in furthur auctions have been eliminated. Sabotage auctions occurring earlier in a *Cutthroat Kitchen* episode involve exceedingly complex dynamic incentives. On the one hand, contestants may want to shade bids down in early sabotage auctions, so that rivals spend their money and exhaust their resources available for later sabotages. On the other hand, contestants may want to overbid to force up rivals' bids to exhaust the resources rivals have for bidding in later rounds. Complicating the dynamics is that contestants may have incomplete information about the number of sabotages they will have to bid on over the course of the competition, which varied across episodes.

The presence of multiple rivals in the first two rounds of an episode adds a further complication, raising the question of which rival to deploy the sabotage against. One strategy may be to concentrate multiple sabotages on one rival, to increase the chance that someone else is eliminated. Another strategy may be to target the rival with the most remaining money, to reduce the chance of eliminating the rival who would be the strongest bidder in later rounds. To estimate the value of the sabotage, the modeler would have to have some idea of the best strategy for deploying the sabotage. Having more than two competitors also raises the issue of free riding. As long as the sabotage is deployed against someone else, a contestant prefers to save resources by having a rival pay for it.

We avoid these complications by modeling the last sabotage auction in an episode when there are only two contestants. This endgame removes any dynamic considerations of how bidding in the current auction would affect strategies in subsequent auctions. It was well established that no more than two sabotages were auctioned in the last round, removing any uncertainty whether there would be additional sabotages after that. The fact that only two contestants remain in the last round removes any ambiguity about which rival to deploy the sabotage against and obviates any free riding. The drawback of focusing on the last round is that we lose the information from the large number of auctions leading up to the last—over six on average—but enough information remains to estimate the parameters of interest fairly precisely.

Let E denote the set of episodes in our data, indexed by $e \in E$. Let I denote the set of contestants in our data, indexed by $i \in I$, consisting of the remaining two contestants in each episode in E. Let v_i denote the additional benefit to i from winning the episode beyond the prize money, termed i's prestige value, possibly including the "warm glow" from winning a competition, acclaim from demonstrating talent, and/or improved job prospects. Improved job prospects could translate into higher future income, thus carrying a monetary value, but we separate this future income from the prize money earned won in the episode. Assume v_i is continuously distributed with probability density function $f(v_i)$, cumulative distribution function $F(v_i)$, mean μ, and standard deviation σ. The focus of our analysis will be to estimate μ and σ.

To help distinguish the winner of a sabotage auction from the winner of the competition, we introduce a set of indicator functions. Let s_i^1 and s_i^2 be indicators for i's winning, respectively, the first and second sabotage auctions held in the last round. Thus, $s_i = s_i^1 + s_i^2$ denotes the total number of sabotages i wins in the last round. Let w_i be an indicator for i's winning the competition.

Turn next to characterizing i's payoff function. Let m_i denote the remaining money that contestant i has after bidding in all the sabotage auctions prior to the last. Let b_i denote i's last bid in the last sabotage auction, setting $b_i = 0$ if i declines to bid for it. To simplify the modeling, we will allow bids to be any positive real number, though the show required bids to be in discrete \$100 increments (which our estimation methodology will account for). The episode winner obtains payoff

$$u_i(m_i - \mathbf{1}(b_i > b_{-i})b_i) + v_i, \tag{1}$$

where u_i denotes i's utility over the monetary prize, a weakly concave function, and $-i$ denotes the remaining rival to competitor i in the competition. The indicator function $\mathbf{1}(b_i > b_{-i})$ reflects the fact that only the sabotage winner pays for it; if the contestant who loses the last sabotage proceeds to win the episode, he or she keeps the entirety of m_i for the prize.

Winning a sabotage improves the relative quality of i's cooking in two ways: by protecting i cooking from being sabotaged and by harming the quality of the rival's cooking. This increase in the relative quality of i's cooking increases the chance that i's dish is judged best in the last round. The contestant with the best dish in the last round wins the episode. Let $p_i(s_i^1, s_i^2)$ denote the probability that i's dish is judged best and thus i wins the episode as a function of whether i won the various sabotages. Assume this function is increasing in both arguments. Define $\Delta_i^1(s_i^2) = p_i(1, s_i^2) - p_i(0, s_i^2)$ as i's performance gain from winning the first sabotage. Conditioning the performance gain from one sabotage on other allows sabotages to be complements or substitutes in the cooking production function. We similarly define i's performance gain from winning the second sabotage as $\Delta_i^2(s_i^1) = p_i(s_i^1, 1) - p_i(s_i^1, 0)$. Performance gains can alternatively be expressed in percentage terms as the following semi-elasticities:

$$\eta_i^1(s_i^2) = \frac{\Delta_i^1(s_i^2)}{p_i(1, s_i^2)} \tag{2}$$

$$\eta_i^2(s_i^1) = \frac{\Delta_i^2(s_i^1)}{p_i(s_i^1, 1)}. \tag{3}$$

Show rules dictate that a contestant cannot bid more than the remaining resources provided by the show, m_i. Contestants are not allowed to dip into resources outside of the show to increase their bids even if they wanted to. Thus, auction rules place the following constraint on contestant's ability to pay:

$$b_i \leq m_i. \tag{4}$$

Let $\bar{b}_i$ denote i's maximum willingness to pay for the last sabotage in the counterfactual absence of any constraint on ability to pay. To compute $\bar{b}_i$, we compare i's expected payoff from winning the sabotage auction by raising his or her bid to $\bar{b}_i$, which by equation (1) equals

$$p_i(s_i^1, 1)[u_i(m_i - \bar{b}_i) + v_i], \tag{5}$$

to i's expected payoff from losing the sabotage auction by standing pat:

$$p_i(s_i^1, 0)[u_i(m_i) + v_i]. \tag{6}$$

Equating (5) and (6) and solving yields

$$\bar{b}_i = m_i - u^{-1}\left(\frac{p_i(s_i^1, 0)}{p_i(s_i^1, 1)} u_i(m_i) - \frac{p_i(s_i^1, 1) - p_i(s_i^1, 0)}{p_i(s_i^1, 1)} v_i\right). \tag{7}$$

Although $\bar{b}_i$ is a latent variable rather than observed in our data, minimal assumptions about rational bidding in an English auction will allow us to bound $\bar{b}_i$ in terms of the last bid by the contestant, b_i, and the rival, b_{-i}, both of which we do observe. Bidding more than one's maximum willingness to pay is weakly dominated for all $i \in I$, implying

$$\bar{b} \geq b_i. \tag{8}$$

Substituting for $\bar{b}_i$ from (7) into (8) and rearranging yields

$$\eta_i^2(s_i^1) \geq \frac{u_i(m_i) - u_i(m_i - b_i)}{u_i(m_i) + v_i}. \tag{9}$$

Intuitively, winning the auction must result in a greater percentage increase in the chance of winning the episode on the left-hand side of (9) than the percentage reduction in bidder's utility on the right-hand side. To transform (9) into a bound on the variable of interest, the prestige value v_i, define the threshold

$$T_i(b) = \frac{u_i(m_i) - u_i(m_i - b)}{\eta_i^2(s_i^1)} - u_i(m_i). \tag{10}$$

For brevity, we have suppressed the dependence of T_i on other variables besides the bid b. Rearranging (9) then yields

$$v_i \geq T_i(b_i). \tag{11}$$

A further bound on $\bar{b}_i$ can be obtained in certain circumstances. Any bidder who lost the sabotage ($b_i < b_{-i}$) but was not liquidity constrained, so could have paid more ($m_i > b_{-i}$) must have valued the sabotage less than the rival's bid ($\bar{b}_i \leq b_{-i}$). Otherwise, bidding just above b_{-i} would have weakly dominated i's observed bid b_i. Formally, for all i such that $b_i < b_{-i} < m_i$,

$$\bar{b}_i \leq b_{-i}. \tag{12}$$

The same logic behind steps (8)–(11) imply $v_i \leq T_i(b_{-i})$.

In sum, our analysis of the model has allowed us to derive bounds on the prestige value v_i in terms of observables. For contestants who conceded the sabotage auction to their rivals despite having enough money to outbid them—that is for i such that $b_i < b_{-i} < m_i$—their prestige values are bounded in an interval:

$$v_i \in [T_i(b_i), T_i(b_{-i})]. \tag{13}$$

For other contestants, the analysis only provides a lower bound on the prestige value:

$$v_i \in [T_i(b_i), \infty). \tag{14}$$

6. Empirical Methodology

Our empirical methodology exploits the information in model equations (13)–(14) to obtain estimates of the parameters of interest via maximum likelihood (ML). The latent variable v_i appears on the left-hand side of (13)–(14); this is the unknown variable of interest for which we seek to estimate the distributional parameters μ and σ. The right-hand side of (13)–(14) depend on $T_i(b_i)$ and $T_i(b_{-i})$. As equation (10) shows, these are functions of the bids b_i and b_{-i}, which are recorded for each observation in the data, the remaining money at the start of the last auction, m_i, also recorded for each observation in the data, performance gain η_i^2, which we will estimate from the data, and parameters entering the utility function u_i, which we will also estimate.

To estimate $\eta_i^2(s_i^1)$, we will assume that the effect of sabotages is homogeneous across episodes: i.e., we will drop the subscript i and write $p_i(s_i^1, s_i^2) = p(s_i^1, s_i^2)$, implying $\eta_i^2(s_i^1) = \eta^2(s_i^1)$. This homogeneity assumption is a reasonable approximation if contestants who make it to the last round are believed to have similar cooking skills and are similarly harmed by sabotages. Even if there is heterogeneity in actual skill and harm, what is relevant for estimation are the contestants' subjective assessments of these, which are arguably homogeneous since they have limited opportunity to observe how each other's cooking responds to sabotages. We acknowledge that contestants may misperceive the gains from winning a sabotage; indeed, a cruical part of the analysis will be to assess how such misperceptions may explain observed distortions in bidding behavior. An estimate $\hat{p}(s_i^1, s_i^2)$ of the probability of winning the episode can be obtained from a linear probability model regressing the indicator for winning the episode w_i on indicators for having won no sabotages, only the first, only the second, or both (or in other words on indicators for various combinations of the values of s_i^1 and s_i^2). Elasticity estimates $\hat{\eta}^1(s_i^2)$ and $\hat{\eta}^2(s_i^1)$ can be derived as nonlinear combinations of the probability estimates $\hat{p}(s_i^1, s_i^2)$ via equations (2)–(3).

We take the utility function to have the constant absolute risk aversion (CARA) form:

$$u_i(m) = \frac{1 - e^{-\alpha_i m}}{\alpha_i}, \tag{15}$$

where $\alpha_i = u_i''(m)/u_i'(m)$ is called the coefficient of absolute risk aversion. Using l'Hôpital's Rule, one can show $\lim_{\alpha_i \downarrow 0} u_i(m) = m$, implying that CARA utility nests risk-neutral preferences for vanishingly small values of the coefficient of absolute risk aversion. CARA utility is widely used in empirical work in economics and finance, including the literature measuring risk preferences in game shows (Gertner, 1993; Metrick, 1995; Fullenkamp, Tenorio, and Battalio, 2003), other gambling settings (Jullien and Salanié, 2000), auctions (Cason, 1995), as well as the broader literature, including classic studies by Paxson (1992), Tuckman and Vila (1992), and Haubrich (1994). Among other advantages, it allows risk preferences to be estimated independently of agents' wealth, for which we lack data. In the interest of parsimony, we assume that contestants share a common coefficient of absolute risk aversion α, which we will estimate along with μ and σ as part of the ML routine.

The likelihood of observing prestige values falling into the intervals events (13)–(14) in the data equals

$$\prod_{\{i|b_i<b_{-i}<m_i\}} \left[F(T_i(b_{-i})) - F(T_i(b_i))\right] \prod_{\substack{\{i|b_i>b_{-i}\} \\ \cup\{i|m_i \le b_{-i}\}}} \left[1 - F(T_i(b_i))\right]. \tag{16}$$

Assuming v_i is normally distributed with mean μ and standard deviation σ and taking natural logs yields log-likelihood function

$$\sum_{\{i|b_i<b_{-i}<m_i\}} \ln\left(\Phi\left(\frac{1}{\sigma}[T_i(b_{-i}) - \mu]\right) - \Phi\left(\frac{1}{\sigma}[T_i(b_i) - \mu]\right)\right) + \sum_{\substack{\{i|b_i>b_{-i}\} \\ \cup\{i|m_i \le b_{-i}\}}} \ln\left(1 - \Phi\left(\frac{1}{\sigma}[T_i(b_i) - \mu]\right)\right), \tag{17}$$

where Φ denotes the standard normal cumulative distribution function. Estimates of the mean and standard deviation of the distribution of prestige values, respectively $\hat{\mu}$ and $\hat{\sigma}$, as well as the coefficient of absolute risk aversion $\hat{\alpha}$ can be obtained by maximizing (17) substituting bids b_i and b_{-i} and starting money m_i observed directly in the data and substituting elasticity estimates $\hat{\eta}^2(s_i^1)$ derived from linear-probability-model coefficients as described in the previous paragraph. Ignoring for the moment that $T_i(b)$ is a nonlinear function of a parameter α to be estimated, the likelihood function in equation (16) is quite standard, an offshoot of the Tobit specification called interval regression, which can be run with a single command in several statistical packages.[5] The specification can be generalized to allow the mean and natural logarithm of the standard deviation to be linear functions, $\mu(\mathbf{x}_i)$ and $\ln \sigma(\mathbf{x}_i)$, of a vector of contestant and auction covariates, $\mathbf{x}_i$.[6] We handle the fact that $T_i(b)$ is a nonlinear function of a parameter to be estimated, α, by applying interval regression to maximize (17) for values of α along a grid and selecting $\hat{\alpha}$ as the grid point maximizing (17).

We mentioned the possibility that contestants may misperceive the marginal effect of sabotages. If contestants systematically overestimate the marginal effect of the last sabotage on winning, this would provide a natural explanation for the overbidding we will see in the last auction. While it is easy to argue that contestants' estimates are noisy, it is harder to see why they would be systematically biased. The fact that the second sabotage auctioned in the last round is much less effective than the first provides a compelling reason for a systematic bias. Behavioral-economics models of selective attention (see Schwartzstein (2014)) posit that players may not consider all important payoff-relevant factors. In our setting, contestants may be inattentive to the difference in strength between the two sabotages, believing they have a roughly symmetric effect. We explore this possibility by estimating what we will label an inattention-to-order model (or inattention model for short) in which contestants do not distinguish between first and second sabotages, taking the probability of winning to be a function $p(s_i)$ of the number of sabotages obtained in the last round, irrespective of order.[7] The probabilities associated with the inattention-to-order model can be estimated from

[5] We employ the INTREG command in Stata 18.

[6] We take $\ln \sigma$ rather than σ to be a linear function of $\mathbf{x}_i$ to ensure $\hat{\sigma}$ is positive. Under this specification, the linear coefficients in $\ln \sigma(\mathbf{x}_i)$ have the interpretation of semi-elasticities. In the case of covariates that are indicator variables, the linear coefficients capture the proportional increase in σ when the indicator is switched from 0 to 1.

[7] We have slightly abused notation by using the same p in the inattention model as we used in the setup of the attention model, which allows the first and second sabotages to have different marginal effects. When p appears with just one

the data using a linear-probability model regressing the indicator for winning w_i on indicators for having won no sabotages, one sabotage, or both sabotages.

To account for possible correlation in constestant strategies in an episode, we cluster the robust standard errors at the episode level. To account for the fact that elasticities $\hat{\eta}^2(s_i^1)$ are not observed but estimated, potentially with some estimation error, we compute the standard errors for all parameter estimates using a bootstrap procedure in which the regression estimating the probabilities used to compute $\hat{\eta}^2(s_i^1)$ is included as a step in the bootstrap.

7. Results

7.1. Winning Probabilities and Beliefs

To determine the extent of overbidding for sabotages, we need to estimate the contribution of sabotages to the probability of winning the episode. To start, we will assume that contestants have rational expectations about the performance benefits of obtaining sabotages, which are consistent with empirical estimates from in the data on average, exhibiting no systematic biases. Table 2 reports the results of linear probability models regressing an indicator w_i for winning the episode on indicators for obtaining different configurations of sabotages. The first column of results regresses w_i on indicators for obtaining no sabotages, only the first, only the second, or obtaining both sabotages. This specification allows the first and second sabotages to have different effects on the probability of winning the episode, as specified by the attention-to-order model of attentive beliefs.

The probability of winning is 32% with no sabotages and 68% with both. The probability of winning with exactly one sabotage is intermediate between these two levels and turns out to differ across the first and second sabotages. The first sabotage is stronger the second: the probability of winning the episode with the first sabotage alone is 58% and only 42% with the second sabotage alone. The first sabotage may be stronger simply because it is in effect for a longer fraction of the

argument, it is taken to refer to probabilities in the inattention-to-order model.

round than the second. Alternatively, the first sabotage may interfere with a a crucial cooking stage that is more difficult to recover from than a later stage in which the contestant is perhaps just putting finishing touches on the dish.

A plausible reason for contestants to overvalue the second sabotage arises if following the behavioral model of Schwartzstein (2014), they are inattentive to certain payoff-relevant factors, in this case the differential effect of the first and second sabotages, believing they are equally effective. The last column in Table 2 estimates the beliefs of a contestant who is inattentive to sabotage order but otherwise are consistent with the data. The model forces the first and second sabotage to have the same effect on the probability of winning by collapsing the individual indicators into a single indicator for obtaining one sabotage. Given that two total sabotages auctioned in the last round, when a contestant obtains exactly one sabotage, his or her rival must also obtain exactly one sabotage. Since one of the two of them must win, the estimated probability of winning with one sabotage is mathematically 50%, as the table verifies.

Table 3 converts the probability estimates into semi-elasticities η appearing in the willingness-to-pay formulas. The semi-elasticies reflect percentage increases in the probability of winning, as opposed to percentage-point increases. Looking at the first column of results, corresponding to the model that is attentive to sabotage order, obtaining the first sabotage increases the probability of winning by 45% over obtaining no sabotages and by 38% when added to the second sabotage. The second sabotage increases the probability of winning by 23% over obtaining no sabotages and by 14% when added to the first sabotage. The first sabotage has double or more of the effect on the probability of winning measured as a semi-elasticity. The semi-elasticities associated with the first sabotage are statistically significantly different from 0 at the 1% level, but those associated with the second sabotage, while economically subtantial, are not statistically different from 0 at conventional levels.

The model in which contestants are inattentive to sabotage order, estimated in the last column of results, yields lower semi-elasticities for the first sabotage and higher semi-elasticities for the second sabotage compared to the model that is attentive to sabotage order. The inattentive contestant believes that the second sabotage increases the probability of winning by 36% over no sabotages and by 26% over the first.

7.2. Results for Combined Episodes

With the semi-elasticies η estimated in Table 3 in hand along with data observed on bids b_i and b_{-i} and starting money m_i, one can compute the thresholds $T_i(b_i)$ and $T_i(b_{-i})$ in equation (10) bounding prestige values v_i. These thresholds factor into the log-likelihood in equation (17) which can be maximized to generate estimates of the mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$ for the distribution of prestige values. The maximum-likelihood parameter estimates are reported in Table 4. To account for the fact that contestant beliefs about the probability of winning the episode embodied in semi-elasticities η are estimated rather than observed, we compute standard errors using a bootstrap procedure. Since the distribution of coefficients obtained from the bootstrap in some cases is not normal but skewed, we report bootstrapped confidence intervals and compute p-values directly from those rather than reporting standard errors and computing p-values from the associated z-statistics.

Consider the first three columns, which report results combining different types of episodes (standard, tournament prelims, and tournament finales) together, treating them as homogenous. The first column assumes contestants hold nunaced beliefs, thus understanding that the second sabotage is not as effective as the first and thus of modest benefit, and are risk neutral, with CARA coefficient $\alpha = 0$. Under these modeling assumptions, the maximum-likelihood estimate of the mean prestige value is \$32,900, significantly different from 0 at the 1% level. Such a high prestige values, on average exceeding the starting money stakes in the competition, are needed to rationalize high bids for the only modestly effective second sabotage: contestants must have some additional value from winning beyond the stakes that they are willing to pay a lot for even a modest increase in the chance of securing.

The second and third columns introduce factors that can account for some of the overbidding for the second sabotage. One factor is risk aversion: the more risk averse the bidder, the more he or she will bid for the sabotage, in effect paying a premium for the insurance the sabotage provides against the adverse outcome of losing. The second column allows for risk aversion, estimating a CARA coefficient as part of the maximum-likelihood procedure. The small estimated CARA coefficient of $\hat{\alpha} = 0.033$ suggests that contestants are fairly close to risk neutral, implying that risk aversion is fairly minor consideration which cannot explain much overbidding. Allowing for risk aversion does not reduce mean prestige value substantially, which remains high at $22,500.

The low estimated level of risk aversion is not an artifact of the functional form assumed for the prestige value distribution (normal), but is non-parametrically identified. Increasing the CARA coefficient beyond some moderate value collapses the interval between the minimum prestige value consistent with the i's observed bid $T_i(b_i)$ and the maximum prestige value consistent with not overbidding the rival $T_i(b_{-i})$ for an increasing proportion of the observations, contributing a prohibitive log-likelihood penalty for such observations not just for the normal distribution of prestige values but for any distribution with support on the positive real line.

The third column, in addition to allowing for risk aversion, assumes contestants subscribe to naive beliefs, believing that the second sabotage is no less powerful than the first, leading contestants to overestimate the effect of the second sabotage because the second is in fact less effective than the first second in the data. Overestimating the value of the second sabotage in this way can account for a considerable amount of overbidding. As shown in Table 3, the semi-elasticities for the second sabotage can be nearly twice as high under naive beliefs as under nuanced beliefs. With less residual overbidding to explain, the estimate of mean prestige value is cut by more than half to $9,300. Still, this is a substantial mean, nearly equal to the average amount of prize money the winner ends up with ($11,000 according to Table 1). Note that risk aversion becomes even less consequential (the CARA coefficient falls to 0.027) when naive beliefs are considered.

7.3. Results by Episode Type

The last three columns allow for distinct prestige values across regular episodes and tournaments, including tournament prelims and finales. The specification includes a constant, the coefficient of which measures the mean prestige value for a regular episode. As indicators for prelims and finales are included alongside the constant, their coefficients can be interpreted as the extra prestige value for the various types of tournament episodes over regular episodes.

The results reveal heterogeneity in prestige values masked in the aggregate results. After breaking out the higher prestige values from tournament episides, mean prestige values in regular episodes remain fairly similar to the aggregate results. In the most conservative specification provided by the last column of results, whcih allow the contestant to be risk averse and inattentive to sabotage order, mean prestige value in regular episodes is \$9,600.

Tournament episodes are associated with substantially higher prestige values than regular episodes. The most conservative estimates of the extra prestige value from tournament episodes are provided by the last column of results. In the same way that allowing the contestant to be risk averse and inattentive to sabotage order can moderate the estimate of mean aggregate prestige values by explaining some of the overbidding, these factors can also moderate the estimate of the extra prestige value from tournament episodes.

In the last column, tournament prelims have an extra mean prestige value of \$6,100 over regular episodes, an economically important difference but one that is not statistically significant at conventional levels. Tournament finales have an extra prestige value of \$35,100 over regular episodes, a difference that is statistically significant at the 10% level. Presumably, the small number of tournament finales limits the stastitical significance of the large coefficient estimate on finales. The total mean prestige value for finales in the most conservative specification is $\$9,600 + \$35,100 = \$44,700$. Tournaments finales can generate considerable attention because they are the culmination of four additional prelims which were widely advertised on the channel, and the winner has a claim to have been the best out of sixteen total tournament contestants. Such episodes can plausibly generate considerable prestige value, and here we see how high prestige values can range in such circumstances.

That we are estimating higher prestige values for episodes for which we predict prestige is higher provides a key check that our methods are not just calculating the residual amount of overbidding and providing an appealing label for it. After accounting for other factors that can contribute to overbidding, the remainder is positively correlated with the predicted prestige of the episode, so appropriately construed as an estimate of prestige value.

Risk aversion, which was only a minor consideration in the specification aggregating episode types is even less of a consideration once episode types are disaggregated. The CARA coefficient is only 0.007 in the specification with nuanced beliefs and an even lower 0.002 in the specification with naive beliefs. With such low estimated levels of risk aversion, specifications allowing for risk aversion hardly change the estimated parameters of the prestige-value distribution compared to the risk-neutral specification.

To help visualize how the estimated distribution of prestige value shifts across different episode types and specifications, Figure 1 graphs the probability density functions based on the estimates in the last three columns of Table 4. Within each panel, moving from standard episodes to prelims to finales, the distribution of prestige values shifts toward higher values and spreads out. The second and third panels illustrate the effect of including risk aversion and inattentive beliefs on the distributions of prestige value by episode type. For all three episode types, those factors shift the distribution toward lower values and reduce its spread. The effect of allowing for risk aversion is barely noticeable; the effect of allowing for inattention to sabotage order is much more substantial. Even after including these factors, the distributions have substantial mass on prestige values in the tens of thousands of dollars.

Our discussion of the results has focused on estimates of the mean prestige values $\hat{\mu}$ and downplayed the standard-deviation estimates $\hat{\sigma}$. The latter are not a pure measure of variation in prestige values; they also reflect other sources of heterogeneity, error, and estimation noise. One important additional source of heterogeneity is in the variety of sabotages auctioned across episodes. Some sabotages may have been more obviously damaging than others or at least perceived to have been by contestants. Contestants may have had different levels of risk aversion. Contestants could have made errors in their bidding strategies. Overall, these additional sources of heterogeneity, bidding error, and estimation error would tend to inflate $\hat{\sigma}$ above the standard deviation of the pure distribution of prestige values, making it difficult to give $\hat{\sigma}$ a structural interpretation. On the other hand, our estimates of mean prestige values $\hat{\mu}$ can be given a structural interpretation to the extent that we have successfully controlled for mean biases and that remaining errors and noise are mean zero white noise.

7.4. Demographic Differences

Table 5 estimates the difference in mean prestige values across different contestant demographics. All specifications include a constant term, so the reported demographic indicators should be interpreted as differences from the omitted demographic category.

The indicators for gender and race are small and statistically insignificant, suggesting little evidence that prestige values differ across those categories.

The indicators for job titles are large in magnitude and statistically significant. They are negative, suggesting that chefs and owners gain less prestige value from winning than the omitted category—a catch-all including a variety of titles within the food industry perhaps a rung down from chef or owner on the career ladder such as home cook, line cook, caterer, culinary instructor, and cake decorator as well as a small number of cases of professions outside the food industry such as teachers, firefighters, or stay-at-home parents. We did not have strong priors about the sign of the chef and owner variables. On one hand, contestants who already have already "made their names" in the profession may have less to gain from winning a cooking show than contestants who are trying to rise in the profession. The negative coefficients on chef and owner variables are consistent with this story. On the other hand, other stories are consistent with positive coefficients. Winning the episode may only gain notice for someone with a sufficiently established reputation. Contestants with established reputations may be richer, and having a lower marginal utility of income, may be willing to sacrifice more prize money for prestige benefits. According to the most conservative specification in the last column of Table 5, chefs experience $6,000 less prestige value than the omitted category and owners $9,500 less.

8. Conclusion

We contribute one of the first economic analyses to quantify how much people are willing to spend to increase their social prestige. Our analysis is based on a hand-collected sample of all available episodes of *Cutthroat Kitchen*, a long-running and popular television show with the unique feature that the cooking competition is periodically stopped to run sabotage auctions. Contestants reveal their prestige values when they bid more than would a revenue-maximizing agent for the increase in the probability of winning provided by the sabotage.

In our most conservative specification, which controls for risk aversion and possibly biased estimates of the marginal effect of a sabotage on the probability of winning, we estimate a mean prestige value of nearly $10,000 for typical episodes and over $35,000 for multi-episode tournaments. While this specification controls for important alternative explanations of overbidding besides prestige value, it may be impossible to control for every alternative. Alternatives such as an endowment effect, bidding fever, or spite could also explain overbidding.

We take several approaches to addressing these threats to identification. We can provide a priori arguments that these threats are less relevant in our setting. The winning bidder does not possess the sabotage in our setting but just uses it for the round, weakening any endowment effects. A handful of auctions precede the one we study, providing an opportunity to temper bidding fever. Our general impression from watching the episodes was that of good-natured competition rather than spite intense enough to lead contestants to bid away a majority of their stake to harm a rival.

More concretely, the heterogeneity in the estimates accords with a prestige-value interpretation. We estimate higher prestige values for tournaments, which are presumably more prestigious than typical episodes. While we estimate few systematic demographic differences in prestige values, we do find that chefs and owners have significantly lower prestige values than others. One interpretation is that others are aspiring in the profession and having more to gain from estabishing a reputation. The heterogeneity across types of episode and job titles is not an obvious consequence of endowment effects, bidding fever, or spite.

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Table 1: Descriptive Statistics for *Cutthroat Kitchen* Data

Variable	Measure	Mean	Standard Deviation	Minimum	Maximum	Observations
Episode type						
• Standard	Indicator	0.80	0.40	0	1	316
• Prelim	Indicator	0.16	0.37	0	1	316
• Finale	Indicator	0.04	0.19	0	1	316
Competition variables						
• Total sabotage auctions	Count	7.3	1.0	5	10	158
• Prize money	Thous. $	11.0	6.1	0.3	45.0	158
Contestant demographics						
• Female	Indicator	0.36	0.48	0	1	316
• White	Indicator	0.66	0.47	0	1	316
• Chef	Indicator	0.69	0.46	0	1	316
• Owner	Indicator	0.07	0.26	0	1	316
Last-auction variables						
• Starting money	Thous. $	13.9	6.6	0.1	45.0	316
• Winning bid	Thous. $	5.0	4.0	0.2	26.0	158
• Highest losing bid	Thous. $	3.7	4.2	0.0	25.0	158

Notes: Descriptive statistics for 158 *Cutthroat Kitchen* episodes used in analysis. Rows with $158 \times 2 = 316$ observations are computed for the two remaining contestants competing in the last round.

Table 2: Estimates of Winning Probabilities

Sabotage indicator	Probability estimated	Attention to sabotage order	Inattention to sabotage order
None	$p(0,0) = p(0)$	0.32^{***}	0.32^{***}
		(0.06)	(0.06)
First alone	$p(1,0)$	0.58^{***}	
		(0.05)	
Second alone	$p(0,1)$	0.42^{***}	
		(0.05)	
Single	$p(1)$		0.50^{***}
			(0.00)
Both	$p(1,1) = p(2)$	0.68^{***}	0.68^{***}
		(0.06)	(0.06)
R^2		0.06	0.04

Notes: Estimates from a linear-probability model using 316 contestant observations. Regresses an indicator for winning episode w_i on a subset of sabotage indicators given in the first column. For each model, an exhaustive set of indicators is included and the constant term omitted to avoid multicolinearity. Robust standard errors accounting for clustering of contestants within the same episode reported in parentheses below coefficient estimates. Significantly different from zero in a two-tailed test at the *10% level, **5% level, ***1% level.

Table 3: Semi-elasticities Derived from Probability Estimates

Variable	Attention to sabotage order	Inattention to sabotage order
$\eta^1(0) = \Delta^1(0)/p(1,0)$	0.45^{***}	
	(0.12)	
$\eta^1(1) = \Delta^1(1)/p(1,1)$	0.38^{***}	
	(0.09)	
$\eta^2(0) = \Delta^2(0)/p(0,1)$	0.23	
	(0.18)	
$\eta^2(1) = \Delta^2(1)/p(1,1)$	0.14	
	(0.11)	
$\eta(0) = \Delta(0)/p(1)$		0.36^{***}
		(0.13)
$\eta(1) = \Delta(1)/p(2)$		0.26^{***}
		(0.07)

Notes: Semi-elasticities computed from the estimates in Table 2. Standard errors computed by applying the delta method to the regressions behind Table 2. Significantly different from zero in a two-tailed test at the *10% level, **5% level, ***1% level.

Table 4: Maximum-likelihood Parameter Estimates

	Combining episode types			Varying parameters by episode type		
Variable	Attention to sabotage order, risk neutral	Attention to sabotage order, risk averse	Inattention to sabotage order, risk averse	Attention to sabotage order, risk neutral	Attention to sabotage order, risk averse	Inattention to sabotage order, risk averse
Prestige-value mean (μ, thousand dollars)						
• Constant	32.9*** (26.6, 39.3)	22.5*** (17.9, 28.5)	9.3*** (3.5, 31.2)	25.9*** (21.8, 30.1)	24.0*** (18.7 27.5)	9.6*** (2.9, 33.2)
• Prelims				11.9 (–4.8, 28.2)	11.3 (–4.0, 26.5)	6.1 (–2.7, 18.8)
• Finales				73.8* (8.6, 119.5)	65.0* (10.6 110.8)	35.1* (1.7, 88.6)
Prestige-value standard deviation ($\ln \sigma$, unitless semi-elasticity)						
• Constant	3.4*** (3.2, 3.6)	3.1*** (2.9, 3.3)	2.6*** (2.3, 3.3)	3.2*** (3.0, 3.3)	3.1*** (2.9, 3.2)	2.6*** (2.3, 3.3)
• Prelims				0.2 (–0.4, 0.6)	0.2 (–0.4, 0.6)	0.2 (–0.4, 0.5)
• Finales				1.1 (–0.3, 1.4)	1.0 (–0.2, 1.4)	1.0 (–0.4, 1.4)
Coefficient of absolute risk aversion (α, unitless semi-elasticity)						
• Constant		0.033*** (0.004, 0.055)	0.027*** (0.002, 0.050)		0.007*** (0.002, 0.028)	0.002*** (0.002, 0.026)
Log-likelihood	–564.4	–558.8	–557.3	–541.6	–541.5	–543.0

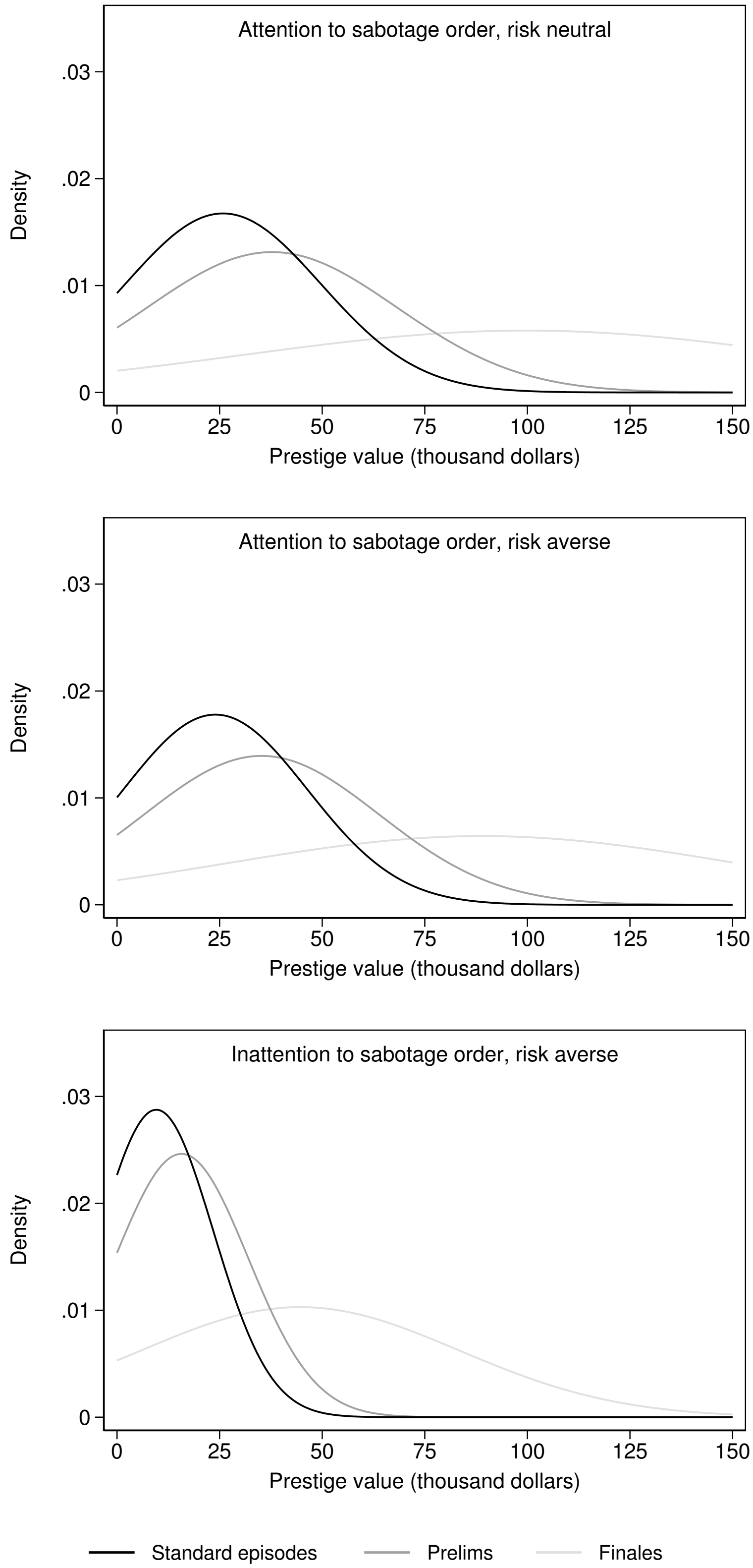
Notes: Estimates from ML procedure positing normal distribution for prestige values using 316 contestant observations. Intervals in parentheses below estimates are 90% confidence intervals based on a bootstrap, clustering on episode, involving 1,000 repetitions. The bootstrap accounts for sampling error in the estimation of winning probabilities. We report confidence intervals rather than standard errors because bootstrapped results are not normal but skewed. Significantly different from zero in a two-tailed test at the *10% level, **5% level, ***1% level.

Table 5: Estimating Demographic Variation in Mean Prestige Value

Variable	Attention to sabotage order, risk neutral	Attention to sabotage order, risk averse	Inattention to sabotage order, risk averse
Prestige-value mean (μ, thousand dollars)			
• Female	−1.1	−1.1	−0.8
	(−6.7, 4.1)	(−6.3, 3.8)	(−4.5, 2.5)
• White	−4.3	−4.1	−2.0
	(−9.6, 0.9)	(−8.7, 1.0)	(−6.6, 1.2)
• Chef	−10.5**	−10.0**	−6.0**
	(−17.4, −3.6)	(−16.6, −3.1)	(−13.2, −2.0)
• Owner	−16.8**	−15.9**	−9.5**
	(−26.3, −4.6)	(−24.8, −4.3)	(−21.1, −2.2)
Log-likelihood	−536.5	−536.4	−538.2

Notes: Estimates from ML procedure positing normal distribution for prestige values using 316 contestant observations, similar to Table 4. All equations also allow mean and standard deviation to vary by episode type as in the last three columns of Table 4, but we only report results for included demographic variables here for brevity. Specification allows mean, but not standard deviation, to vary by demographics. Other notes from Table 4 apply.

Figure 1: Distribution of Prestige Values Graphed by Episode Type



Notes: Densities computed based on estimates from the last three columns of Table 4.