

Expertise in Online Markets

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We examine the effect of the presence of expert buyers on other buyers, the platform, and the sellers in online markets. We model buyer expertise as the ability to accurately predict the quality, or condition, of an item, modeled as its common value. We show that nonexperts may bid more aggressively, even above their expected valuation, to compensate for their lack of information. As a consequence, we obtain two interesting implications. First, auctions with a “hard close” may generate higher revenue than those with a “soft close.” Second, contrary to the linkage principle, an auction platform may obtain a higher revenue by hiding the item’s common-value information from the buyers. We also consider markets where both auctions and posted prices are available and show that the presence of experts allows the sellers of high-quality items to signal their quality by choosing to sell via auctions.

Keywords: competitive strategy; segmentation; pricing; sniping; online auctions; signaling

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1. Introduction

The advent of online auctions, such as those in eBay, led to the first massive-scale deployment of simple second-price auction mechanisms for consumer products. Even though eBay started as a platform for consumer-to-consumer auctions for selling items out of one’s garage, it is now a large selling platform enabling over \$200 billion commerce volume and reaching over 200 million users annually (Koetsier 2013). The addition of posted-price sales has fueled this growth by allowing it to serve as a competitor to other online retail sites. The growth of this new segment of online markets that combine auctions with posted prices raises important new questions about the optimal strategies for buyers and sellers as well as questions about the best design of the platform.

The eBay auction format enforces a “hard close” or ending time at which the item is sold to the highest (winning) bid. In the hours leading up to closing time, the auction is open and simulates the open outcry English auction. If all bidders had only private values, traditional auction theory dictates that the dominant strategy for every bidder is to bid up to his true value. To enable this, eBay offers a proxy bidding tool that allows a bidder to specify his maximum value, and the tool automatically bids the minimum bid increment above the current highest bid (as long as it is below the bidder-specified value). Thus, it was something of a paradox when a majority of eBay auctions exhibited sniping—the phenomenon where

a bidder submits his only bid in the last few seconds of the auction, thus avoiding any response from other bidders.

While several explanations for this behavior have been advanced, one of the most intuitive and accepted ones is that of experienced bidders (Wilcox 2000) or dealers/experts (Roth and Ockenfels 2002). For example, Roth and Ockenfels (2002, p. 1095) argue, and provide empirical evidence, that the existence of sniping in online markets is partly due to buyers’ heterogeneity in their experience with online markets and their expertise in the product category: “[T]here may be bidders who are dealers/experts and who are better able to identify high-value antiques. These well-informed bidders... may wish to bid late because other bidders will recognize that their bid is a signal that the object is unusually valuable.”

In this line of reasoning, the item auctioned off is assumed to have a common value, which these experts have a better knowledge of, and submitting a sniping bid is a way for experts to withhold this information to reap the advantage of this information asymmetry in the resulting price. While several papers have subsequently built upon and refined this explanation of sniping (Bajari and Hortacsu 2003, Rasmusen 2006, Ockenfels and Roth 2006, Hossain 2008, Ely and Hossain 2009), all of them have examined the phenomenon only from the bidders’ perspective. More broadly, to the best of our knowledge, no

other paper has studied the strategic impact of buyers' heterogeneity in expertise (which causes the sniping behavior) on the platform and sellers' strategies in online markets. In this paper, we examine the effect of the existence of expert buyers on *all* of the stakeholders in online markets: the expert and nonexpert buyers, the sellers, and the platform. We discuss the following research questions:

1. How do nonexpert buyers adjust their strategies to compete with experts?
2. How does the presence of experts affect the platform revenue?
3. How does the presence of experts affect the sellers' strategies in online markets?

1.1. Our Contributions

First, we show that the presence of experts encourages the nonexperts to bid more aggressively. In particular, we show that because of the sniping strategy of the expert buyers in hard-close auctions, nonexpert buyers have to bid more than their expected value; otherwise they only win items of low quality against the expert buyers. Quantifying this, we show in Proposition 1 that the higher the proportion of experts among the bidders, the more aggressively the nonexperts bid above their expected value for the item.

Next, we consider the impact of the presence of experts on the platform's strategies. In particular, should the platform maintain the hard-close format for the auction, which allows the experts to snipe, rather than switch to the "soft-close" format? Also, if the platform knows the quality value of the item and can credibly reveal it to the buyers, should it commit to sharing this information with them? We find interesting answers to these questions. Regarding the first question, at the outset, it appears that the hard-close format may hurt platform revenue since without the sniping behavior of experts, nonexpert buyers could respond to bids of experts, and the item would sell at a higher price. Since the platform's fee is usually a fixed fraction of the selling price, the platform would then have an incentive to favor the soft-close format.¹ Contrary to this expectation, we show that the aggressive bidding behavior of the nonexperts that we describe above implies that the platform's overall revenue *increases* in the hard-close format for a wide range of parameter values (Proposition 2). This is a potential new explanation as to why online auction companies such as eBay² retain the hard-close auction format from a revenue perspective. We note, however, that the strategic choice of

soft- versus hard-close format is a complex decision affected by competition among auction platforms as well as a variety of other bidder considerations such as the avoidance of potentially costly bidding wars in hard-close auctions. Our observation above exposes a new facet in a variety of such potential explanations for the popularity of this format.

This result has another important and interesting implication regarding the second question: the platform can benefit from committing to withholding the quality information (Corollary 1). This is in contrast to the celebrated *linkage principle*³ (Milgrom and Weber 1982) and is driven by buyers' heterogeneity in their level of expertise. Proposition 1 can also be interpreted as a reverse *winner's curse*. In auctions with common values, bidders bid lower than their valuation to avoid the winner's curse. However, our result shows that when bidders are heterogeneous in their level of information, noninformed bidders bid more than their valuation to make up for their lack of information.

Finally, we consider the impact of the presence of expert buyers on the sellers' strategies. In particular, we investigate the choice of selling mechanisms between the auction and a posted price sale when they are both available (as is common in most online auction houses). In the presence of expert buyers, under certain conditions, we show that by selling in an auction, a seller can credibly signal⁴ the quality value of his item (Proposition 3). By selling in an auction, the seller shows that he can rely on the *market* (specifically, on the expert buyers) to decide the value of the item. This is a risk that a seller with a low-quality-value item cannot take. Furthermore, this signaling is possible only if there are enough experts, who know the value of the item, in the market. Otherwise, the seller of a high-quality-value item will not be able to separate himself from the seller of a low-value item. In other words, the existence of experts in the market allows the sellers of high-quality products to separate themselves by selling in auctions. This finding is in line with auction houses' claim that auctions increase buyers' confidence. For example, Fraise Auction⁵ argues that one of the benefits of selling in auction is that the "competitive bidding format creates confidence among the buyers when they see other people willing to pay a similar amount for the property." To the best of our knowledge, this result is a new explanation for the popularity of auctions in certain product categories. We reiterate that

¹ In fact, some auction platforms, such as the now defunct Amazon Auctions and Trademe, removed sniping by implementing a soft close that automatically extended the auction time whenever a bid is submitted.

² EZsniper.com provides an extensive list of auction sites with a hard close.

³ The linkage principle argues that the auction house always benefits from committing to revealing all available information.

⁴ Note that the signal that we discuss here is the seller's choice of the selling mechanism. This is different from bids by other bidders, which can also be signals of the quality of the product.

⁵ <http://fraiseauction.com/why-auction/> (accessed January 24, 2016).

the strategic choice of auction versus posted-price is a complex decision affected by several factors. Our observation above proposes a new explanation for why some sellers may choose to use auctions.

Taken together, we initiate the first comprehensive study of the effect of the presence of expert buyers in online markets featuring auctions with a hard close and posted prices, and establish the following results.

1. Nonexpert buyers must adjust their strategies in response to experts' sniping, and, under certain conditions, have to bid more than their expected value in hard-close auctions in equilibrium.

2. As a consequence, the platform revenue is higher in the hard-close auction than in the soft-close format for a wide range of parameter values.

3. Finally, the presence of experts in markets with hard-close auctions and posted prices allows the seller of high-quality items to credibly signal the quality of the item by selling in the auction and separating himself from sellers of low-quality items who sell using posted prices, under certain conditions.

Note that despite the explosive growth of auctions, particularly in the consumer-to-consumer arena, our findings are relevant mainly to items with a significant common value component (such as collectibles, antiques, art, and used items of uncertain quality).

In what follows, we review related literature. Section 2 introduces the main model, Section 3 solves the equilibria of the model with a hard close, and Section 4 compares them with the corresponding equilibria of the auction with a soft close, which does not allow for sniping. In Section 5 we analyze the sellers' game of choosing among selling formats. We conclude the paper in Section 6. All proofs and further details are relegated to the appendices.

1.2. Related Literature

Our work relates to the literature on online auctions with common values and a hard close, intermediaries' incentives to reveal product quality information, sellers' strategies to signal product quality, and the advantages and disadvantages of auctions versus posted prices. In the following, we review the related literature on each topic.

Bajari and Hortacsu (2003) argue that last-minute bidding is an equilibrium in a stylized model of eBay auctions with common values. They develop and estimate a structural econometric model of bidding in eBay auctions with common value and endogenous entry. Wilcox (2000) and Rasmusen (2006) use common values to model sniping and bidders' behavior on eBay auctions. Wilcox (2000) shows that sniping increases as buyers' experience increases. Furthermore, the increase in the sniping behavior of the more experienced bidders is more pronounced for the type

of items that are more likely to have a common value component. Similarly, a model with no common value as in Yoganarasimhan (2013) demonstrates no sniping behavior. Rasmusen (2006) considers a model where bidders incur a cost for learning the common value of the item. As a result, those who acquire the information snipe to hide their information from other bidders. Similar to the previous literature,⁶ sniping emerges as an equilibrium strategy in our model as well. However, our focus is the effect of the presence of experts on nonexperts', sellers', and the platform's strategies and revenues, which is crucially missing in the earlier literature. Glover and Raviv (2012) show that when sellers can choose between hard- and soft-close formats, soft close leads to a higher revenue, and experienced sellers are more likely to choose soft close. We discuss their result in Section 5, and show that soft close emerges as the unique pooling equilibrium if sellers can choose the closing format. Our result provides a new theoretical explanation for their empirical findings. In contrast to earlier work by Ockenfels and Roth (2006), who show an example in which seller revenue is lower at the equilibrium for hard close than in the soft-close case, in our model, we show that the hard-close format increases revenue compared to the soft-close format. More specifically, we provide an explanation as to why online auction companies such as eBay retain the auction format that allows for sniping from a revenue perspective that takes into account the aggressive bidding behavior of the nonexperts.

In this paper, we show that an intermediary could benefit from withholding information about the quality of the items in an auction. This is in contrast with the well-known linkage principle by Milgrom and Weber (1982). The linkage principle argues that the auction house always benefits from committing to reveal all available information. The intuition behind the principle is that revealing the information can mitigate the winner's curse and motivates the buyers to bid more aggressively. We arrive at the contrast due to buyers' *heterogeneity* in terms of their information about the quality value of the item, as modeled by their expert status. More specifically, the result of Milgrom and Weber (1982) is established when valuation of bidders depend *symmetrically* on the unobserved signals of the other bidders, a condition that is not satisfied in our setup.⁷ Withholding information,

⁶ The literature on trying to explain sniping in online auctions is vast. Other than previously mentioned papers, see also Ockenfels and Roth (2006), Hossain (2008), Wintr (2008), and Ely and Hossain (2009).

⁷ Failure of the linkage principle has also been argued in a few other papers in the auction theory literature. For example, Perry and Reny (1999), Krishna (2009), and Fang and Parreiras (2003) show the failure in setups with multiple items, ex ante asymmetries, and budget constraints, respectively.

under certain circumstances, has also been shown to increase social welfare, by Zhang (2014), in the context of product labeling. Gal-Or et al. (2007) show that, under certain conditions, a buyer benefits from withholding information in procurement schemes.

Many researchers in marketing have studied signaling unobserved quality under information asymmetry. Moorthy and Srinivasan (1995) and Soberman (2003) show that sellers can use warranties such as money-back guarantees to signal the quality of their items. Bhardwaj and Balasubramanian (2005) show that by letting the customers request information about an item, rather than revealing it without solicitation, a seller can signal the quality of his item. Mayzlin and Shin (2011) show that uninformative advertising, as an invitation for search, can be used to signal product quality. Li et al. (2009) investigate auction features such as pictures and reserve price that enable sellers to reveal more information about their credibility and product quality, and empirically examine how different types of indicators help alleviate uncertainty. Finally, Subramanian and Rao (2016) show that, by displaying daily deal sales, a platform can leverage its sales to experienced customers to signal its type and attract new customers. This is relevant to our result as in both Subramanian and Rao's paper and our paper, the existence of experts (or experienced customers) can help the sellers to extract more revenue from the nonexpert customers. However, the higher revenue is achieved using very different tools, displaying daily deal sales versus selling in auctions, in the two papers. Compared to the previous literature, we introduce a new dimension for sellers to signal the quality of their items. In particular, for product categories with a common value component where assessing the common value needs expertise (e.g., in the antiques category), we show that selling via auction can signal that the item has a high common value.

Finally, we review the related literature that compares auctions to posted price selling mechanisms. Einav et al. (2013) propose a model to explain the shift from Internet auctions to posted prices and consider two hypotheses: a shift in buyer demand away from auctions, and general narrowing of seller margins that favors posted prices. By using eBay data, they find that the former is more important. There is a significant economics literature that compares auctions to posted price mechanisms. Notably, Wang (1993) compares auctions with posted prices and shows that auctions become preferable when buyers' valuations are more dispersed. In another important paper, Bulow and Klemperer (1996) have shown that the additional revenue one can obtain by attracting one more bidder in an auction without reserve price is greater than the additional revenue by setting the optimal reserve

price, hence in a sense establishing that "value of negotiating skill is small relative to the value of additional competition" (p. 180). In an empirical work, Bajari et al. (2009) conclude that the choice of sales mechanism may be influenced by the characteristics of the product being sold. To the best of our knowledge, our paper is the first work that considers the signaling effects of the choice of the mechanism on buyers' beliefs. Specifically, we show that the choice of selling mechanism can be used by sellers of high-quality items as a signal of their item's quality.

2. Model

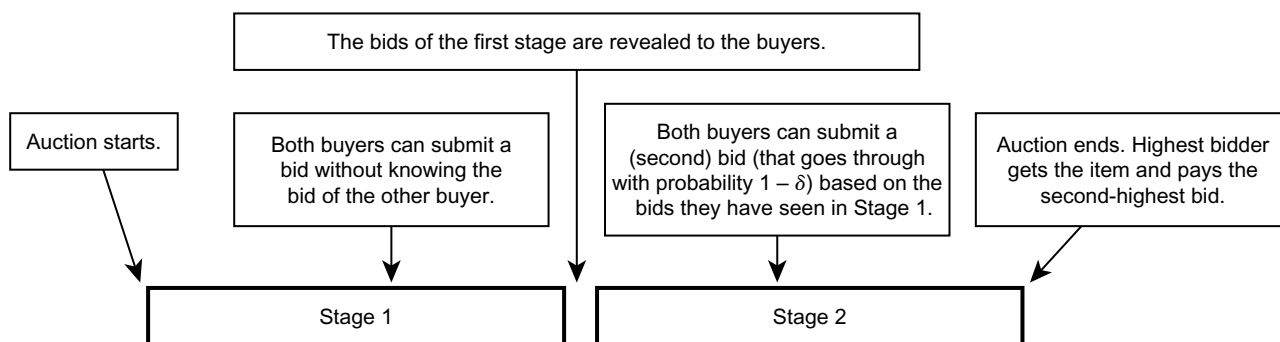
We consider a model with two buyers and one item. We assume that there are two types of buyers, *experts* and *nonexperts*, and each buyer is an expert with probability p . Given anonymity of online marketplaces, we assume that each buyer does not know whether his opponent is an expert or not.⁸

In our model the items sold in online auctions have differing levels of "quality value," which may reflect the condition of a used good or the relative efficacy of a product among its competitors. Note that this value is similar to a common value in that its benefit accrues equally to both expert bidders (who can accurately predict quality value) and nonexpert bidders (who do not know the quality value). We assume that the quality value, denoted by a binary random variable C with realizations 0 and $c > 0$, is known only by experts and is the same for both experts and nonexperts (therefore, it can be described as a common value). Moreover, the items sold in online auctions also have differing levels of "private value," which may reflect bidders' private tastes for the items, or whether they have immediate needs for the items. Each bidder may have a different private value. We assume that the private value, denoted by a binary random variable V with realizations 0 and $v > 0$, is learned privately by both experts and nonexperts.

The total value of the item for a bidder is the sum of the quality value and an additional private value component. More specifically, we assume that C has a binary distribution: $\Pr(C = c) = q$ (high common value) and $\Pr(C = 0) = 1 - q$ (low common value), also V (for each bidder) has a binary distribution: $\Pr(V = v) = r$ (high private value) and $\Pr(V = 0) = 1 - r$ (low private value). We assume that c , v , p , q , and r are common knowledge. Moreover, buyers' private value types are privately known by all buyers, and the realization of C is privately known only by experts (nonexperts know only the prior probability

⁸ On eBay and most other auction platforms, identities of bidders are revealed only after an auction ends. Furthermore, bidders can easily hide their type by creating and using a new account online.

Figure 1 Timeline of the Game



distribution). The total value of the item for each bidder is simply $C + V$, where C is the quality value of the item and V is the buyer's specific private value.

We model the online auction with a hard close as a two-stage bidding game where the second stage represents the very last opportunity to submit a bid (the sniping window), while the first stage represents the whole window of time preceding the close. Even though in practice the period before the sniping window is a dynamic game, we model it (Stage 1) by allowing each bidder to submit a single bid: to reconcile this with reality, we can think of the highest bid that a bidder submitted before the sniping window as the first-stage bid. Bidders can observe competitors' bids of Stage 1 and respond to them in Stage 2; however, they do not have enough time to respond to competitors' bids of Stage 2. It is worth mentioning that we can derive all of our results with a more realistic dynamic game model of the first stage.⁹ However, though it is a bit more involved, it does not add any further insight to our analysis, so we use the simpler two-stage formulation here.

Motivated by the fact that bidding in the sniping window has the risk of losing the bid due to erratic Internet traffic, we assume that a bid in Stage 2 goes through only with probability $1 - \delta$ for sufficiently small $\delta \geq 0$. Throughout the paper, we assume that $0 \leq \delta \leq \bar{\delta}$ where $\bar{\delta}$ is defined in Section A.3 of the appendix. This assumption implies that the risk of the bid not going through, due to δ , is not large enough to outweigh the benefit of sniping for experts. We provide an example of equilibrium structure when $\delta > \bar{\delta}$ in Section B.2 of the online appendix (available as supplemental material at <http://dx.doi.org/10.1287/mnsc.2016.2530>).

The assumption of small δ is also consistent with industry numbers that show that the rate of failure of sniping bids is less than 1%.¹⁰

The timing of the model is as follows (see also Figure 1). Before Stage 1, each buyer knows his own type (expert or nonexpert), but not the type of the other buyer. If a buyer is an expert, he also knows the common value (whether $C = 0$ or $C = c$). All buyers also know their buyer-specific private values (whether $V = 0$ or $V = v$). In Stage 1, both buyers simultaneously submit their bids. After Stage 1 and before Stage 2, both buyers observe the other buyer's bid and may be able to infer their opponent's type (and values). In Stage 2, both buyers simultaneously decide if they want to increase their bid from Stage 1, and if so by how much. In other words, bids of Stage 2 have to be greater than or equal to bids of Stage 1. Stage 2 bids are received by the auctioneer with probability $1 - \delta$. If the bid of Stage 2 is lost for a bidder (with probability δ), the auctioneer continues to use the bid of Stage 1 for that bidder. After Stage 2, the item is given to the buyer with the highest bid at the price of the second-highest bid. If there is a tie between two bidders of different values, then the item goes to the one of higher value; if both have the same value but are of different types, the tie is broken in favor of the nonexpert; if both bidders have the same value and type, the tie is broken randomly.¹¹

In auctions with a soft close, there are possibly an infinite number of stages. If a bid is submitted at any stage, bidders can submit another bid in the next stage. The game ends when no bid is submitted in some stage. We also consider posted prices in Section 4. In this game, the seller posts a price z and the bidders then decide whether to buy at this price. The trade takes place at the posted price z if and only if at least one bidder is interested in the item. If both bidders want the item, each of them gets the item with probability $\frac{1}{2}$. Finally, in both types of auctions, soft and hard close, and in posted price, we assume that

⁹ We can consider a dynamic auction in the time interval $[0, 1)$ and sniping at time 1.

¹⁰ For example, see <https://www.quicksnipe.com/faq.php> (accessed January 24, 2016).

¹¹ For a full description and motivation of the tie-breaking rule, see Section B.3 of the online appendix. We demonstrate that our results continue to hold if we change the rule to break the tie in favor of experts rather than nonexperts.

the platform fee is a constant fraction ξ of the selling price and is paid by the seller.

3. Effect of Experts on Buyer Strategies

In this section, we describe the equilibria of the auction game (a formal complete treatment is in Section A.1 of the appendix). We derive conditions under which experts use sniping, in equilibrium, to protect their information about the common value of the item. Furthermore, we show that, under certain conditions, nonexperts with high private value bid aggressively—even above their expected valuation—to compete with experts.

We call an expert/nonexpert with high/low private value a *high/low expert/nonexpert*. Our main lemma characterizing the equilibrium (Lemma 2 in the appendix) splits the values of v into nine ranges depending on the relative values of c , v , p , r , and q . Our characterization labels the strategies for each of the four types of players as one of five different behaviors: (i) a *sniping* strategy is adopted only by experts and involves mimicking the nonexperts in the first stage and bidding their true value only in the second stage; (ii) a *truthful* strategy involves bidding the truthful (expected) value and revising it in the second stage under any additional relevant information; (iii) an *aggressive* strategy is adopted only by high nonexperts and involves bidding over the expected value to have a chance of winning against the experts—we discuss this strategy in detail in Section 3.2; (iv) a *mixed* strategy is a mixed version of the truthful and aggressive strategies; (v) an *underbidding* strategy is used only by low nonexperts, where they bid lower than their expected value for the item.

3.1. Experts Induce Sniping

Lemma 2 presents necessary and sufficient conditions for each of the above strategies to emerge in equilibrium for each type of bidder. In particular, we show that low experts use the sniping strategy if and only if $v \leq c \cdot (1-p)(1-q)r / (2pq(1-r) + (1-p)r)$, while high experts always use a sniping strategy.

Note that the expression

$$c \cdot \frac{(1-p)(1-q)r}{2pq(1-r) + (1-p)r}$$

is decreasing in q and p , and increasing in r and c . In other words, a low expert's incentive to snipe increases as p or q decrease, and as r or c increase.

To see why, first note that a low expert snipes only if the common value is high. A low value of p (i.e., there are few experts in the market), a low value of q (i.e., there are few high-quality items in the market), or a high value of c (i.e., quality difference between

low-quality and high-quality items is large), all indicate that the low expert's information, that the common value is high, is *valuable*. This motivates the low expert to snipe and hide this information. Therefore, as p decreases, q decreases, or c increases, the threshold on v for the low expert to snipe increases. Moreover, a high value of r indicates that the opponent is likely to have a high private value. Therefore, as r increases, the probability that the low expert would win the item *without* sniping decreases, which increases his motivation to snipe. As a result, as r increases, the threshold on v for the low expert to snipe increases.

3.2. Impact of Experts on Nonexperts' Strategy

A high nonexpert's optimal strategy depends on the value of v . If v is sufficiently high ($cq + v \geq c$), a high nonexpert's expected value for the item is higher than c . In this case, high nonexperts always win the competition against low experts. For smaller values of v , the situation is more interesting. By bidding their expected value against experts, high nonexperts win only when the common value is low. Therefore, high nonexperts have to bid higher than their expected value (aggressive strategy and mixed strategy) to win a high-common-value item against low experts. Note that bidding above the expected value does not necessarily mean that they have to pay more than their expected value, because the auction format is second price. The only risk is that if two high nonexperts compete with each other, they may both bid above their expected value and end up paying more than their expected value. In this case, a nonexpert's payoff could be negative. Our first proposition discusses the conditions under which nonexperts bid more than their expected value.

PROPOSITION 1. *If the expected value of a high nonexpert for the item is less than the common value of the item (i.e., $cq + v < c$), the high nonexpert may bid more than his valuation for the item in equilibrium. Moreover, the probability of overbidding increases as the fraction of experts in the market (i.e., p) increases.*

Proposition 1 shows that if the value of v is high enough, nonexperts always take the risk of over paying, and bid above their expected value in order to win against experts. However, if v is not sufficiently large, a nonexpert over bids only with some probability (depicted in Figure 2). This mixed strategy allows the nonexperts to mitigate the risk of over paying due to competition with another nonexpert. Furthermore, Proposition 1 shows that as the probability p that the opponent is an expert increases, a nonexpert's willingness to take the risk and bid above his expected value increases (depicted in Figure 3).

Figure 2 Probability That a High Nonexpert Overbids as v Increases for $p = 0.3$, $r = 0.5$, $q = 0.1$, and $c = 1$

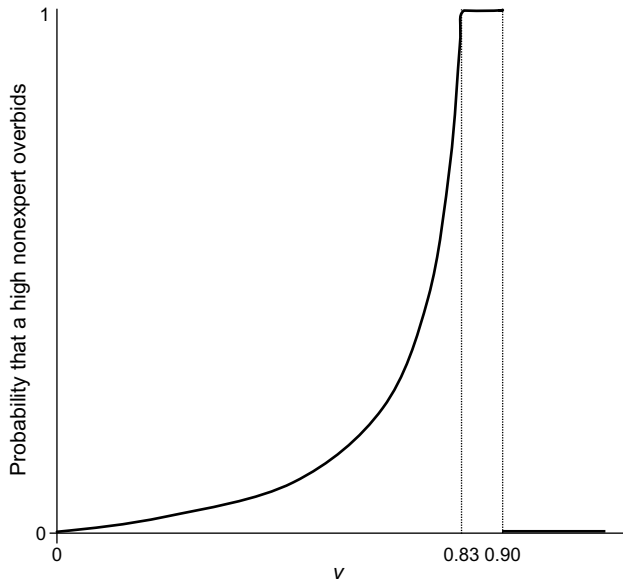
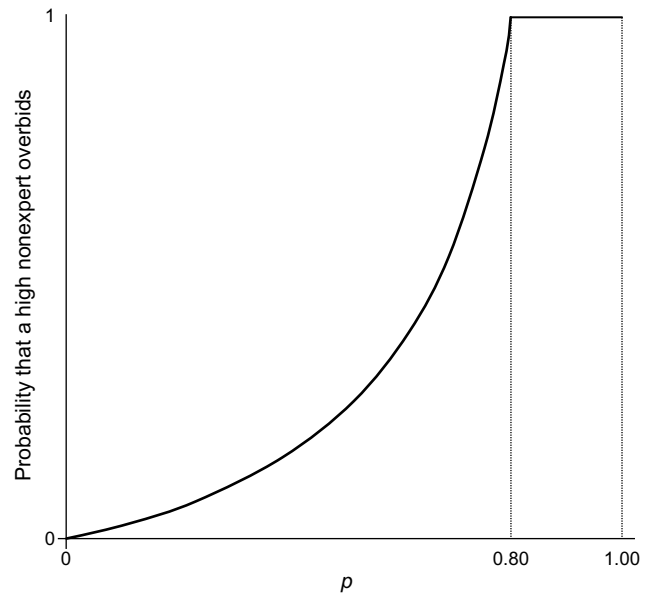


Figure 3 Probability That a High Nonexpert Overbids as p Increases for $v = 0.5$, $r = 0.5$, $q = 0.1$, and $c = 1$



4. Effect of Experts on Platform Strategies

An important assumption in Proposition 1 is that experts can hide their information by sniping. The platform can eliminate sniping by extending the duration of the auction whenever a bid is submitted (this is the soft-close auction format). In this case, nonexperts always have enough time to respond to experts' bids and, therefore, do not have to bid above their expected valuation.

We show that, under certain conditions, nonexperts' aggressive behavior leads to higher revenue for the platform to the extent that the platform benefits from allowing sniping (by enforcing a hard close). In other words, experts' ability to hide their information forces the nonexperts to bid more aggressively and ultimately leads to higher revenue for sellers and for the platform. This result also relates to platform strategies regarding the revelation of information. In Section 4.3 we show the breakdown of the *linkage principle* by showing that the platform may benefit from withholding quality information from the buyers when the buyers are heterogeneous in their level of expertise.

4.1. An Auction with a Soft Close

We now consider a model in which sniping is not possible. One way to prevent sniping is by extending the duration of the auction by a few minutes every time there is a bid near the current end time of the auction. This auction is called an auction with a soft close and was used by the now defunct Amazon Auctions. A way to model this is by starting with a game that has only one stage and every time there is a

bid during the current stage, the auction extends for one more stage. In other words, every time someone makes a bid, the other buyers can see it and respond to it. In Section 4.2, we first characterize the equilibrium for a model of soft-close auctions (the details are in Lemma 3 in Section A.2 of the appendix). Then we compare seller's revenue and the platform's revenue across the two models. The goal is to see which ending rule results in better revenues for the sellers (and therefore for the platform).

4.2. Effect of Experts on Platform Revenue

Here we summarize the key implications of Lemma 3 that appears in the appendix: When the soft-close format is used, high nonexperts bid their expected value. If they see a bid of c , they infer that the opponent is a low expert and the common value is high. In that case, they increase their bid to c to win the item at price c . On the other hand, with soft close, experts always reveal the value of a high-common-value item to nonexperts. This increases the nonexperts' willingness to pay and in some cases leads to higher revenue for the seller. However, when there is a soft close, nonexperts do not have to bid above their valuation. This reduces the competition and can hurt sellers' revenue as well as the platform's revenue. In Lemma 1 we see that sellers can benefit from a hard close under certain conditions. We use this lemma to analyze the platform's incentive in having a hard close.

LEMMA 1. *When $cq + v < c$, the seller of an item with low common value always has higher expected revenue in a hard close than in a soft close, whereas the seller of an*

item with high common value has higher revenue in hard than soft close if and only if p is sufficiently large.

Lemma 1 shows that the seller of an item with low common value always benefits from a hard close. This is intuitive because a hard close causes sniping, which prevents the flow of information from experts to non-experts. Therefore, when there is a hard close, non-experts are more likely to overpay for an item with low common value. The interesting part is that even the seller of an item with high common value benefits from a hard close if p is high enough. This is because when there is a hard close, nonexperts know that they will not be able to infer the common value, and therefore have to bid more aggressively to win the item. As we observe in Proposition 1, this aggressive bidding behavior increases as p increases. If p is sufficiently large, the positive effect of this aggressive bidding behavior on seller's revenue can dominate the negative effect of the lack of information flow and result in higher revenues for the seller of a high-quality item with a hard close than with a soft close. Using the same argument, we can see that the platform can also benefit from a hard close when p is sufficiently large. This result is formalized in Proposition 2.

PROPOSITION 2. *If the expected value of the high non-experts for the item is less than the common value of the item (i.e., $cq + v < c$), and the fraction of experts in the market (i.e., p) is sufficiently large, the platform's revenue from a hard close is higher than that from a soft close.*

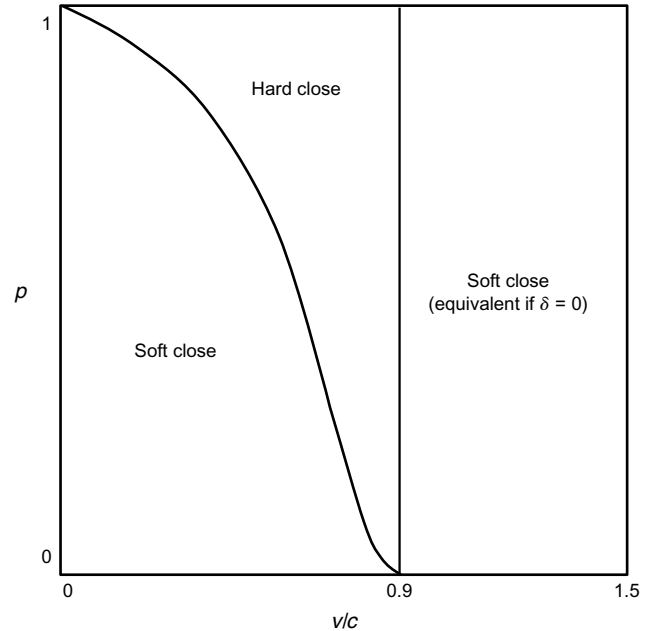
A graphical illustration of Proposition 2 is depicted in Figure 4. When $cq + v < c$ ($v/c < 0.9$ in the figure), the region where a hard close provides higher revenue appears when v is sufficiently larger than c , and p is sufficiently large. This is because higher v and higher p both lead to nonexperts' aggressive bidding, as we saw in Figures 2 and 3 and Proposition 1.

Proposition 2 shows that for some items the platform's revenue is higher in a hard close, while for other items the revenue is higher in a soft close. Ideally, the optimal strategy for a platform would be to use different policies for different items. However, in practice, platforms may have to use the same policy for all items for other reasons (e.g., consistent user experience). Therefore, the optimal policy will depend on the distribution of the items and the volume of the transactions across the parameter space.

4.3. Experts and the Breakdown of the Linkage Principle

Finally, we discuss the connection between the hard-close format and revelation of information in the marketplace. Note that a hard close allows the experts to protect their information about the value of the item. We know that the platform sometimes benefits from a hard close. This could suggest that the

Figure 4 The Regions Are Labeled with the Format That Provides Higher Revenue for the Platform (for $r = 0.5$ and $q = 0.1$)



Note. Note that $0.9 = 1 - q$.

platform may also benefit from *withholding information* about the value of the item. This is an important implication because it is in contrast with the well-known “linkage principle” in auction theory Milgrom and Weber (1982).

The linkage principle states that auction platforms (e.g., auction houses) benefit from committing to reveal all available information about an item, positive or negative. The platform revealing the information reduces the downside risk of winning the item, also known as the winner's curse. But we show that there is also a downside in revealing the information in the presence of heterogeneous bidders, and the platform may sometimes benefit from committing to not revealing the information.

Our result shows that when bidders are *asymmetric* in terms of their information about the value of the item, bidders with less information have to bid more aggressively; otherwise, they only win the item when bidders with more information do not want the item (i.e., the common value is low). This aggressive behavior incentivizes the platform to withhold any information about the quality value of an item. This result is formalized in the following corollary.

COROLLARY 1. *In auctions with hard close, for medium values of p and v/c , committing to reveal the common value to the buyers decreases platform's revenue.*

We should note that the region in Figure 4 where the hard-close format provides higher revenue is the same as the region in Corollary 1 in which the platform prefers to withhold the common value information.

Our model is different from the model in Milgrom and Weber (1982) in several aspects. However, the breakdown of the linkage principle is due to only two differences in modeling assumptions. First, we allow the bidders to be heterogenous in terms of their information about the value of the item. Second, bidders do not know how much information other bidders have in this regard. We can show that even in a sealed bid second price auction, a special case of the model in Milgrom and Weber (1982), introducing these two aspects can lead to the breakdown of the linkage principle. Furthermore, both of these aspects are required for the linkage principle to break down. In particular, if bidders are asymmetric in terms of how much information they have about the value of the item, but they *know* how much information other bidders have (e.g., whether the opponent is an expert or not), Campbell and Levin (2000) establish that the linkage principle still holds.

Finally, note that Corollary 1 applies only to settings in which the platform has access to some valuable information about the item that is not easily available to all the bidders. For example, using historical market data, eBay provides a quality score for used items in certain categories. Another example is the free vehicle history reports that eBay provided for some time but later discontinued.¹²

So far we have discussed the effect of the existence of experts on nonexperts' and the platform's decisions. In Section 5, we analyze the effect of experts on sellers' choice of selling mechanism. In particular, we show that the existence of experts can help the sellers of items with a high common value to signal the value of their items to nonexperts.

5. Effect of Experts on Seller Strategies

In this section, we show that the existence of experts in the market could help the sellers to signal the quality/common value of their item to nonexperts. We look at sellers' choice of selling mechanism between an auction and a posted price sale.¹³ We call the seller of an item with high common value a high-type seller, and the seller of an item with low common value a low-type seller. A seller is high-type with probability q , where q is common knowledge. A seller naturally knows his own type; experts also know the seller's type (since they know the common value of items being offered). But nonexperts do not know the

seller's type. We investigate whether a seller can signal his type using the selling mechanism (auction versus posted price). In particular, we derive conditions for the existence of a separating equilibrium. We show that existence of enough experts in the market is a necessary condition for a separating equilibrium to exist; furthermore, when the fraction of experts in the market, p , is sufficiently large, a separating equilibrium exists only for moderate values of v/c .

A seller sets his selling mechanism M (posted price or auction). In case of posted price, M also includes the price. For a mechanism M , we assume that all nonexperts have the same belief about a seller who uses M . In general, nonexperts' belief about a mechanism is the probability that they think a seller using that mechanism is a high type. However, since we consider only pure strategy Nash equilibria of the game, the nonexperts' belief about a mechanism is limited to three possibilities: low (L), high (H), and unknown (X). In belief L , nonexperts believe that a seller using mechanism M is always a low-type seller. In belief H , nonexperts believe that a seller using mechanism M is always a high-type seller. Finally, in belief X , nonexperts cannot infer anything about the seller's type and believe that the seller is a high type with probability q .

Nonexperts have beliefs about each mechanism M . In equilibrium, the beliefs must be consistent with the sellers' strategies. In particular, if both types of sellers use the same mechanism in (a pooling) equilibrium, the nonexperts' belief for that mechanism must be X . If the two types of sellers use different mechanisms in (a separating) equilibrium, the nonexperts' belief for the mechanism used by the low-type seller must be L and for the mechanism used by the high-type seller must be H . Furthermore, in an equilibrium, given the nonexperts' beliefs, sellers should not be able to benefit from changing their strategies.

Note that sniping is relevant only when the buyers' belief about some mechanism M is X . Therefore, in a separating equilibrium, the platform's decision on whether to use a soft or hard close does not affect buyers' equilibrium behavior or sellers' strategies. In other words, the following analysis applies to both soft- and hard-close cases.

In general, signaling games can have infinitely many equilibria, supported by different out-of-equilibrium beliefs in the game. Therefore, proving just the existence of an equilibrium with certain characteristics may not be a strong result. To further strengthen the support for our result that selling in auction can be used by high-type sellers as a signal of quality, we show that, under certain conditions, such an equilibrium is the only separating equilibrium that survives the "intuitive criterion" refinement. The intuitive criterion, introduced by Cho and Kreps (1987),

¹² <http://announcements.ebay.com/2009/11/free-vehicle-history-reports-on-ebay-motors/> (accessed January 24, 2016).

¹³ In Section B.5 of the online appendix, we further consider the seller's choice of closing format (hard versus soft) as a signaling mechanism.

is an equilibrium refinement that requires out-of-equilibrium beliefs to place zero weight on types that can never gain from deviating from a fixed equilibrium outcome. The intuitive criterion has been used in various signaling papers in the marketing literature including, but not limited to, Simester (1995), Desai and Srinivasan (1995) and Jiang et al. (2011).

Proposition 3 shows that when the fraction of experts in the market is sufficiently large and the value of v/c is moderate, there exists a unique separating equilibrium in which a high-type seller chooses an auction and a low-type seller chooses posted price as their respective selling mechanisms. A proof and related analysis are provided in Section A.4 of the appendix. Figure 5 shows the regions in which this separating equilibrium exists and is unique as a function of p and v/c .

Let us define

$$\nu_1 = \min\left(\frac{(1-p)(1-p(1-2r(1-r)))}{2r(1-r)}, \frac{(1-p)^2}{2(1-p(1-p))(1-r)r}\right),$$

$$\nu_2 = \min\left(\frac{(1-pr)^2}{r(p(2-pr)-r)}, \frac{1}{2r(1-r)}\right),$$

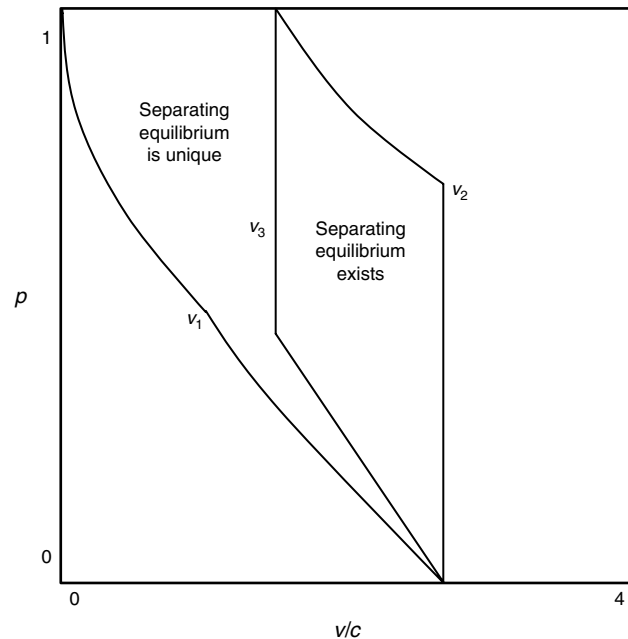
$$\nu_3 = \min\left(\frac{1-r}{2r}, \frac{(1-p)(2-r(1-p))}{r(4+(2-p(2-p))r^2-2r(3-p))}\right).$$

PROPOSITION 3. *If $v/c \in [\nu_1, \nu_2]$, there exists a separating equilibrium in which a high-type seller uses an auction and a low-type seller uses a posted price v . Furthermore, if $v/c \in (\nu_1, \nu_3)$, this is the only separating equilibrium that survives the intuitive criterion refinement. Finally, there exists no separating equilibrium in which a low-type seller uses an auction.*

The proof and a more elaborate discussion of Proposition 3 are relegated to the appendix. The intuition behind the proof of Proposition 3 is as follows. First, note that in general, an auction is more favorable to a high-type seller than a low-type seller. This is because, in auctions, the price is determined by bidders, and expert bidders do not bid high when the seller is low-type. This allows the high-type seller to separate himself from the low-type seller by selling in an auction. But for this separating equilibrium to exist, the low-type seller's incentive to mimic has to be sufficiently low and the high-type seller's incentive to separate has to be sufficiently high. These two forces give us the thresholds ν_1 and ν_2 for existence (and ν_3 for uniqueness under IC refinement) of this equilibrium.

In a separating equilibrium, even nonexperts know that the low-type seller is a low type. Hence, nonexperts are willing to pay at most v for the item sold by the low-type seller. Therefore, the low-type seller's

Figure 5 The Existence and Uniqueness of a Separating Equilibrium in Which the High-Type Seller Uses Auction and the Low-Type Seller Uses Posted Price, Assuming $r = \frac{1}{4}$



incentive to mimic increases as v or p decreases. If p and v are sufficiently small, since the low-type seller's incentive to mimic is sufficiently large, a separating equilibrium does not exist. This is captured by condition $v/c \geq \nu_1$ in Proposition 3, and is represented by the left contour in Figure 5.

On the other hand, as v/c increases, the common value matters less, and the high-type seller's incentive to signal his type (and to separate himself) decreases. When v/c is large enough, we show that the high-type seller chooses to sell via an auction only if p is sufficiently small. This gives us the second condition for existence of this separating equilibrium, namely, $v/c \leq \nu_2$. The condition for uniqueness of the equilibrium, $v/c \leq \nu_3$, follows a similar intuition.

It is interesting to note that the seller's strategy in a separating equilibrium, and the conditions for existence of this equilibrium, do not depend on q . Intuitively, this is because buyers can always infer the seller's type in a separating equilibrium; therefore, when considering the seller's strategy and possible out-of-equilibrium deviations, the ex ante probability that the seller is a high type does not matter.

A Note on Hard- vs. Soft-Close Formats. In this section, motivated by eBay's platform, we studied sellers' choice of auction versus posted price. It is theoretically interesting to know what happens, when limited to using auctions, if sellers can choose between hard- and soft-close formats.¹⁴ This is the

¹⁴We are grateful to an anonymous referee for suggesting this question.

mechanism that was employed by the now defunct Yahoo Auctions. In Section B.5 of the online appendix, we show that if sellers can choose between soft- and hard-close formats, the only equilibrium that survives D1 criterion refinement¹⁵ is the one in which both types of sellers use the soft-close format (as a pure strategy pooling equilibrium). Furthermore, nonexperts' belief in the hard-close format will be low. This implies that sellers who choose the hard-close format (out of equilibrium) will earn less revenue in expectation. Our results are consistent with the empirical findings of Glover and Raviv (2012) that show that the soft-close format leads to higher revenue than the hard-close format, and that sellers with less experience are more likely to use the hard-close format. Our explanation, however, is different from theirs, as we attribute the revenue difference to buyers' beliefs and the underlying signaling mechanism as opposed to sniping.

6. Conclusion

In this paper, we examined important questions for the buyers, sellers, and the platform of an online market supporting auctions and posted prices. We answered questions about optimal behavior for each of them using the well-documented presence of expertise among the bidders as the key underlying assumption. In particular, we studied the impact of the presence of expert bidders in online markets using a simple model of auctions with a hard close and posted prices. Motivated by large number of *used* items sold in online markets such as eBay.com, we supposed that items have differing levels of "quality" (which we model as common values), and different bidders have different capacities (which we model as expertise) to predict the quality. Bidders with low expertise may be affected by bids earlier in the auction, as these can be interpreted as signals for the quality of the item. In our model, sniping emerges as an equilibrium strategy for experts to hide their information about the quality of the item in hard-close auctions.

Our results provide several important managerial implications.

- We show that, as a consequence of sniping behavior in equilibrium by the experts in hard-close auctions, nonexpert buyers with less information have to bid aggressively, i.e., more than their expected value. This result highlights the compensatory behavior adopted by the large majority of bidders (nonexperts) that arises endogenously in these common marketplaces.

¹⁵ Intuitively, D1 equilibrium refinement requires out-of-equilibrium beliefs to be supported on types that have the most to gain from deviating from a fixed equilibrium. For an extended discussion, see Fudenberg and Tirole (1991, Section 11.2).

- Surprisingly, given the aggressive behavior of nonexperts, the platform's revenue can be *higher* in hard-close auctions (where sniping is prevalent) than in soft-close auctions (where sniping cannot happen). This is a new, as-yet unexplored addition to the variety of explanations of why many online auction sites use the hard-close format rather than the soft-close format.

- Another interesting implication of nonexperts' aggressive behavior is that the platform can benefit in its revenue from committing to hide the information. This result has important managerial implications, as it suggests that when buyers are heterogeneous in terms of their information about the value of the item, the linkage principle does not always hold.

- When sellers can choose between auction and posted-price formats, a seller may be able to signal the high quality (or authenticity) of his item to the buyers by selling in an auction and thus separate himself from low-quality-item sellers as long as there are enough experts in the market. This provides useful guidance to vendors in such markets, where the magnitude and extent of these decisions can be moderated based on the degree and extent of the presence of expert buyers in the mix. This result also provides a new explanation for the success of auctions in categories such as antiques, art, and collectibles, where common value and therefore expertise are important.

Collectively, our work sheds light on the important differences that arise when knowledgeable or expert buyers are introduced to online marketplaces, and it leads to useful guidelines for all participants in such markets.

Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/mnsc.2016.2530>.

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Appendix

In this appendix, we present detailed explanations of the results. First, we discuss the analyses and proofs of Sections 3 and 4, in Sections A.1 and A.2, respectively. Then, we provide details of the role of the parameter δ in our model in Section A.3. Finally, in Section A.4, we detail the results

of Section 5. Some of the proofs and longer discussions are relegated to the online appendix.

A.1. Analyses and Proofs of Section 3

In this section, we formally characterize the equilibria of the auction game.

Based on the relation of the parameters c, v, p, r , and q , we split the set of possible parameter values into nine mutually exclusive and collectively exhaustive ranges. In the first four ranges, we have that $cq + v < c$ and $v < cq$; in the next two, we have $cq + v < c$ and $v \geq cq$; in the next two, we have $cq + v \geq c$ and $v < cq$, and in the last range, we have $cq + v \geq c$ and $v \geq cq$.

Consider the function

$$f(c, p, r, q) = c \cdot \frac{(1-p)(1-q)r}{2pq(1-r) + (1-p)r}.$$

Let $m_1 = f(c, p, r, q)$, $m_2 = f(c, p, 1-r, 1-q)$, $M_1 = f(c, p, 1, q) = c \cdot (1-q)$, and $M_2 = f(c, p, 1, 1-q) = c \cdot q$. It is easy to verify that $m_1 \leq M_1$ and $m_2 \leq M_2$. We consider nine different cases as follows: $v \in [0, \min\{m_1, m_2\})$, $v \in [m_1, \min\{m_2, M_1\})$, $v \in [m_2, \min\{m_1, M_2\})$, $v \in [\max\{m_1, m_2\}, \min\{M_1, M_2\})$, $v \in [M_2, m_1)$, $v \in [\max\{m_1, M_2\}, M_1)$, $v \in [M_1, m_2)$, $v \in [\max\{m_2, M_1\}, M_2)$, and $v \in [\max\{M_1, M_2\}, +\infty)$.

To describe an equilibrium, we use the notation (s_1, s_2, s_3, s_4) , which means that a high expert follows the strategy s_1 , a low expert follows the strategy s_2 , a high nonexpert the strategy s_3 , and a low nonexpert the strategy s_4 . For the bidding strategies of each type we use the following notation:

- For a high expert, consider the following strategies:
 - s_1^{HE} : If $C = 0$, he bids v in the first stage and does nothing in the second stage. If $C = c$, he bids $cq + v$ in the first stage and bids $c + v$ in the second stage (sniping strategy).
 - s_2^{HE} : If $C = 0$, he bids v in the first stage and does nothing in the second stage. If $C = c$, he bids c in the first stage and bids $c + v$ in the second stage (sniping strategy).
- For a low expert, consider the following strategies:
 - s^{LE} : If $C = 0$, he does nothing. If $C = c$, he bids $cq + v$ in the first stage and c in the second stage (sniping strategy).
 - t^{LE} : If $C = 0$, he does nothing. If $C = c$, he bids c in the first stage and nothing in the second stage (truthful strategy).
- For a high nonexpert, consider the following strategies:
 - x^{HNE} : He bids $cq + v$ in the first stage. If he sees a bid other than 0, v, cq , or $cq + v$ in the first stage, he bids $c + v$ in the second stage. Otherwise, he bids c in the second stage with probability $1 - a$, where $a = 1 - 2p(1-r)qv / ((1-p)r(c - (cq + v)))$ (mixed strategy).
 - o^{HNE} : He bids c in the first stage. If he sees a bid other than 0, v, cq , or c in the first stage, he bids $c + v$ in the second stage. Otherwise, he does nothing in the second stage (aggressive strategy).
 - t^{HNE} : He bids $cq + v$ in the first stage. If he sees a bid other than 0, v, cq, c , or $cq + v$ in the first stage, he bids $c + v$ in the second stage (truthful strategy).
- For a low nonexpert, consider the following strategies:
 - x^{LNE} : He bids v in the first stage. He bids cq in the second stage with probability $1 - g$, where $g = (2pr(1-q)v / ((1-p)(1-r)(cq - v)) - \delta) / (1 - \delta)$ (mixed strategy).

- u^{LNE} : He bids v in the first stage and nothing in the second stage (underbidding strategy).
- t^{LNE} : He bids cq in the first stage and nothing in the second stage (truthful strategy).

We describe equilibrium bidding strategies for buyers in the nine cases in the following lemma.

LEMMA 2. For the auction model described in Section 2, the buyers' equilibrium bidding strategies are given below.

1. If $v \in [0, \min\{m_1, m_2\})$, the set of strategies $(s_1^{\text{HE}}, s^{\text{LE}}, x^{\text{HNE}}, x^{\text{LNE}})$ forms an equilibrium.
2. If $v \in [m_1, \min\{m_2, M_1\})$, the set of strategies $(s_2^{\text{HE}}, t^{\text{LE}}, o^{\text{HNE}}, x^{\text{LNE}})$ forms an equilibrium.
3. If $v \in [m_2, \min\{m_1, M_2\})$, the set of strategies $(s_1^{\text{HE}}, s^{\text{LE}}, x^{\text{HNE}}, u^{\text{LNE}})$ forms an equilibrium.
4. If $v \in [\max\{m_1, m_2\}, \min\{M_1, M_2\})$, the set of strategies $(s_2^{\text{HE}}, t^{\text{LE}}, o^{\text{HNE}}, u^{\text{LNE}})$ forms an equilibrium.
5. If $v \in [M_2, m_1)$, the set of strategies $(s_1^{\text{HE}}, s^{\text{LE}}, x^{\text{HNE}}, t^{\text{LNE}})$ forms an equilibrium.
6. If $v \in [\max\{m_1, M_2\}, M_1)$, the set of strategies $(s_2^{\text{HE}}, t^{\text{LE}}, o^{\text{HNE}}, t^{\text{LNE}})$ forms an equilibrium.
7. If $v \in [M_1, m_2)$, the set of strategies $(s_1^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, x^{\text{LNE}})$ forms an equilibrium.
8. If $v \in [\max\{m_2, M_1\}, M_2)$, the set of strategies $(s_1^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, u^{\text{LNE}})$ forms an equilibrium.
9. If $v \in [\max\{M_1, M_2\}, +\infty)$, the set of strategies $(s_1^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, t^{\text{LNE}})$ forms an equilibrium.

The proof of Lemma 2 is relegated to Section B.1 of the online appendix.

PROOF OF PROPOSITION 1. This result comes directly from Lemma 2. We can see that when $m_1 \leq v < M_1$, nonexperts overbid all the time, and when $v < m_1$, they overbid with some probability. We can check in the proof of Lemma 2 that the probability of over bidding is $1 - a = 2p(1-r)qv / ((1-p)r(c - (cq + v)))$. It is easy to see that this is an increasing function on p . \square

A.2. Analyses and Proofs of Section 4

Expert strategies for soft-close auctions. As before, for the bidding strategies of each type of buyer, we use the following notation:

- For a high expert, consider the following strategy:
 - t^{HE} : If $C = 0$, he bids v in the first stage and nothing later. If $C = c$, he bids $c + v$ in the first stage and nothing later (truthful strategy).
- For a low expert, consider the following strategy:
 - t^{LE} : If $C = 0$, he does nothing. If $C = c$, he bids c in the first stage and nothing later (truthful strategy).
- For a high nonexpert, consider the following strategy:
 - t^{HNE} : He bids $cq + v$ in the first stage. If he sees a bid of c or $c + v$ at some point and $cq + v < c$, he bids c in the next stage (truthful strategy).
- For a low nonexpert, consider the following strategies:
 - x^{LNE} : He bids v in the first stage. In the second stage, he bids cq with probability $1 - w$, where $w = 2pr(1-q)v / ((1-p)(1-r)(cq - v))$, and nothing later (mixed strategy).
 - u^{LNE} : He bids v in the first stage and nothing later (underbidding strategy).

— t^{LNE} : He bids cq in the first stage and nothing later (truthful strategy).

LEMMA 3. In a platform with soft close,

1. if $v \in [0, m_2]$, the set of strategies $(t^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, x^{\text{LNE}})$ forms an equilibrium;
2. if $v \in [m_2, M_2]$, the set of strategies $(t^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, u^{\text{LNE}})$ forms an equilibrium;
3. if $v \in [M_2, +\infty)$, the set of strategies $(t^{\text{HE}}, t^{\text{LE}}, t^{\text{HNE}}, t^{\text{LNE}})$ forms an equilibrium.

PROOF. With soft close, an expert is going to bid his true valuation at some point, because anything less than the true valuation will result in a lower payoff. If there is a non-expert opponent, he is going to respond to that; therefore, the expert may as well bid truthfully from the first stage. More specifically, the strategies for the experts will be as follows:

- *High expert*: If $C = 0$, bids v in the first stage and nothing later. If $C = c$, bids $c + v$ in the first stage and nothing later (strategy t^{HE}).
- *Low expert*: If $C = 0$, does nothing. If $C = c$, he bids c in the first stage and nothing later (strategy t^{LE}).

For the high nonexpert, the strategy is simple as well. He will bid his expected valuation in the first stage, which is $cq + v$. If the opponent bids c or $c + v$ in the first stage (or at some later point), he will understand that he is an expert and that $C = c$; therefore, if $cq + v < c$, he will bid c in the next stage (the minimum possible bid that maximizes his payoff). This is strategy t^{HNE} .

If $cq \leq v$ (i.e., $v \geq M_2$), then a low nonexpert will bid his expected valuation in the first stage, which is cq , and then he will not do anything (strategy t^{LNE}). Because, even if, for example, he sees a bid of c and realizes that the common value is high, by bidding c and winning the item, his payoff is still 0.

If $v < cq$ (i.e., $v < M_2$), then a low nonexpert doesn't want to bid cq from the beginning because if the opponent is a high expert and $C = 0$, he will end up with negative payoff. So, he bids v in the first stage, i.e., the maximum he can without the risk above, and waits. If he sees a bid other than v from the opponent, he will lose anyway, so it doesn't matter what strategy he will follow next, and we assume he will follow the same strategy as if he sees a bid of v . If he sees a bid of v , then he bids cq in the second stage with probability $1 - w$. No matter what happens in the second stage, he does nothing in the third stage. We need now to calculate the probability w .

First of all, if he does nothing in the second stage and he sees a bid of cq , he realizes that the opponent is another low nonexpert, but there is no reason to bid something higher because his expected payoff will be 0. If the opponent does not bid as well, then the auction ends, and there is no third stage. Therefore, his payoff, if he sees a bid of v in the first stage and he does nothing in the second, is

$$\frac{pr(1-q)}{pr(1-q) + (1-p)(1-r)}(0) + \frac{(1-p)(1-r)}{pr(1-q) + (1-p)(1-r)} \left(w \frac{cq-v}{2} + (1-w)0 \right).$$

opponent is high expert and $C=0$
opponent is low nonexpert

If he bids cq in the second stage, his payoff is

$$\frac{pr(1-q)}{pr(1-q) + (1-p)(1-r)}(-v) + \frac{(1-p)(1-r)}{pr(1-q) + (1-p)(1-r)}(w(cq-v) + (1-w)0).$$

opponent is high expert and $C=0$
opponent is low nonexpert

We need these two expressions to be equal, from which we get

$$w = \frac{2pr(1-q)v}{(1-p)(1-r)(cq-v)}.$$

This is always nonnegative, and it is < 1 iff

$$v < \frac{c(1-p)(1-r)q}{2pr(1-q) + (1-p)(1-r)} = m_2.$$

Therefore, if $v < m_2$, the low nonexpert follows the strategy x^{LNE} .

If $v \geq (c(1-p)(1-r)q)/(2pr(1-q) + (1-p)(1-r)) = m_2$ (and $v < M_2$), then it is sub optimal to bid cq , therefore we set $w = 1$ (strategy u^{LNE}). \square

PROOF OF LEMMA 1. For a low seller, a hard close is always better, because the bid of every bidder is greater than or equal to his bid when there is a soft close.

For a high seller, we know from Proposition 1 that as p increases, high nonexperts bid more and more aggressively. This makes the revenue higher as p increases, in the hard-close format. Therefore, to show the result, it is enough to show that for $p \approx 1$ the revenue with hard close is better than the revenue with soft close.

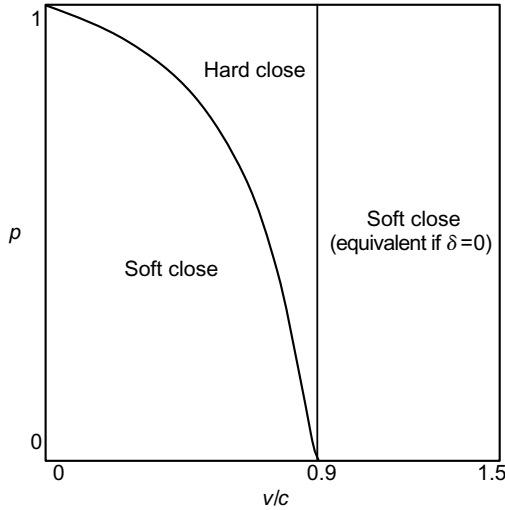
When $p \approx 1$, it holds that $m_1 \approx m_2 \approx 0$; therefore there are only two relevant equilibria in Lemma 2 (cases 4 and 6, since it is also $v < M_1$) and two in Lemma 3 (cases 2 and 3). Case 4 of Lemma 2 corresponds to case 2 of Lemma 3 and case 6 of Lemma 2 corresponds to case 3 of Lemma 3. We can see that all bids are the same in both models except the bids of the high nonexpert, which are higher with a hard close (the high nonexpert is overbidding in the equilibria 4 and 6 of Lemma 2). Therefore, overall the expected revenue is higher for a high seller with the hard-close format.

This is also illustrated in Figure A.1, which shows which policy gives higher revenue to the high seller in different regions of the parameter space. Notice that this is slightly different from Figure 4, which refers to the platform's revenue. \square

PROOF OF PROPOSITION 2. This result follows directly from Lemma 1. Since a low seller always benefits from a hard close, and a high seller benefits for large p , the expected platform's revenue is better with a hard close for sufficiently large p . \square

The analogue of Figure 4, where the format that provides the higher revenue is labeled as a function of other parameters in the model, is presented in Figure A.2. In particular, in Figure A.2(a) we can see that as r (the probability that a bidder has high private value) increases, the region where a hard close provides higher revenue becomes smaller. This is because from the perspective of a high nonexpert, high r means higher probability that the other bidder is a high

Figure A.1 The Regions Show Whether a Hard Close Provides Higher Revenue for a High Seller (for $r = 0.5$ and $q = 0.1$)



Note. This figure is slightly different from Figure 4 in that this compares formats that provide higher revenue for a high seller versus the earlier figure that does the same for the overall platform revenue.

nonexpert too, which in turn means lower willingness to bid aggressively in the hard-close format. This results in lower revenue for a hard close when r is large.

PROOF OF COROLLARY 1. When the platform reveals the common value to everyone, all bidders bid their true valuation. Therefore, in the region in which the aggressive bidding of high nonexperts makes hard close better than soft close for the platform (the middle region in Figure 4), the platform prefers to hide the common value so that the high nonexperts keep bidding higher than their true valuation. \square

A.3. Upper-Bound Condition on δ

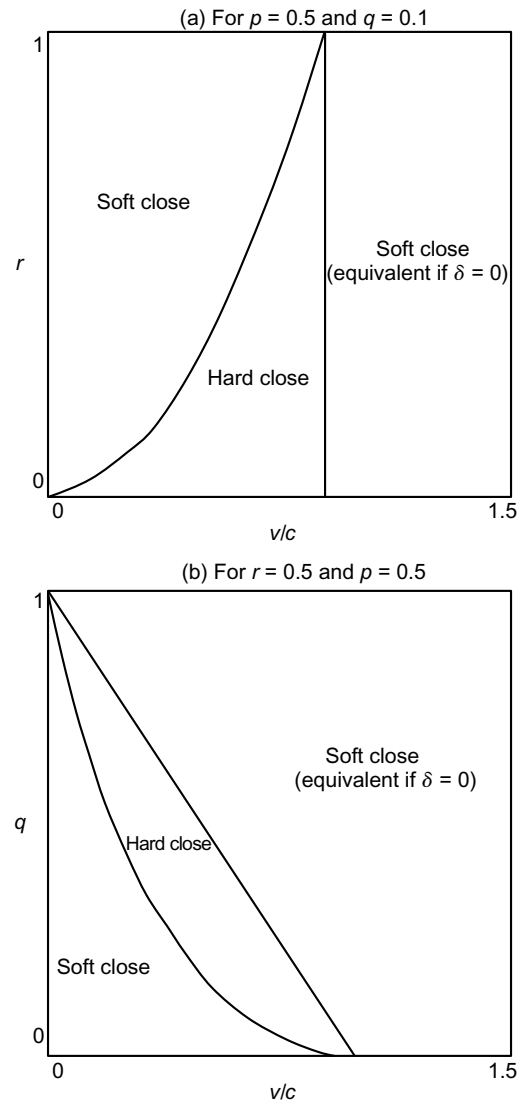
In our model we assume that δ is sufficiently small, i.e., $\delta \leq \bar{\delta}$. This upper-bound condition is calculated as the minimum of at most three different thresholds coming from the indifference conditions for the three of the types of players: high experts, low experts, and low nonexperts. These are the conditions that reflect the relations between the parameter values at which the current set of strategies are no longer in equilibrium. Intuitively, when $\delta > \bar{\delta}$, the cost of sniping (i.e., the risk that the bid does not go through) outweighs its benefits. Therefore, some types of bidders decide not to snipe. Since other types of bidders know this, they also have to update their strategies. As a result, we get different (and several cases of) equilibrium structures for $\delta > \bar{\delta}$. We provide an example of this in Section B.2 of the online appendix.

A thorough discussion and calculation of the thresholds for $\bar{\delta}$ is deferred to Section B.2 in the online appendix. The exact definition of $\bar{\delta}$ is given in Lemma 4. To provide some intuition, in Figure A.3 we present plots of $\bar{\delta}$ as a function of v , of p , of q , and of r .

A.4. Analyses and Proofs of Section 5

We use the following notation to explain the results of this section: Let $\pi_T^B(M)$, where $T \in \{L, H\}$ and $B \in \{L, H, X\}$

Figure A.2 The Regions Are Labeled with the Format That Provides Higher Revenue for the Platform



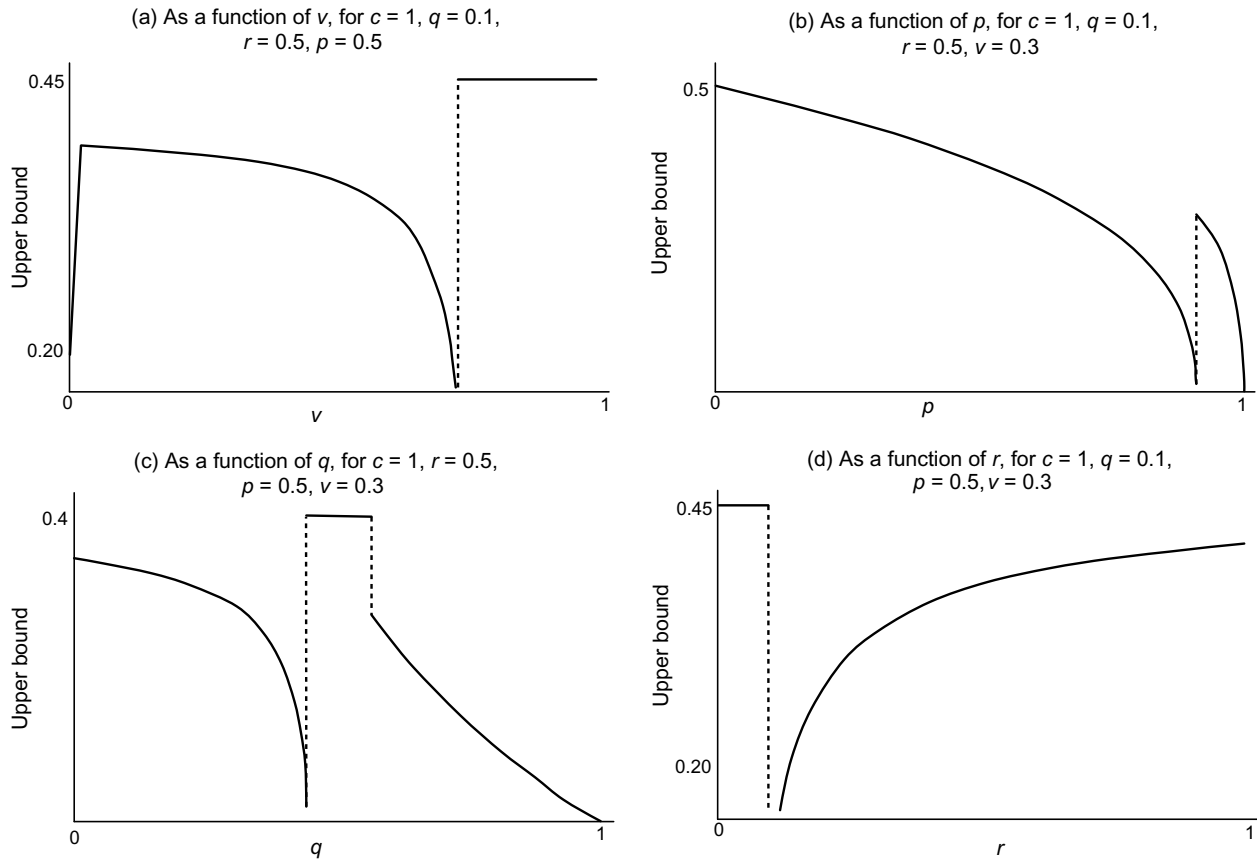
Note. This figure is an analogue of Figure 4, presenting the same result for other parameter variations.

denote the expected profit of a seller who uses mechanism $M \in \{A, (B, z)\}$ (where A denotes auction, and (B, z) denotes posted price where the price is z), has type T , and nonexperts believe has type B . Let M^{pool} be the mechanism that both types of sellers use in a pooling equilibrium.

The revenue of a high- or low-type seller in an auction, where nonexperts have belief high or low, is given in the following formulas. Recall that p is the probability of being expert, and r is the probability of having high value.

$$\begin{aligned} \pi_H^H(A) &= c + r^2v, \\ \pi_L^L(A) &= r^2v; \\ \pi_H^L(A) &= \begin{cases} cp^2 + rv(2(1-p)p(1-r) + r) & \text{if } v \leq c, \\ cp(2(1-p)r + p - 2(1-p)r^2) + r^2v & \text{if } v > c; \end{cases} \\ \pi_L^H(A) &= \begin{cases} c(1-p)^2 + rv(2(1-p)p(1-r) + r) & \text{if } v \leq c, \\ c(1-p)(p(2(1-r)r - 1) + 1) + r^2v & \text{if } v > c. \end{cases} \end{aligned}$$

Figure A.3 Plots of the Upper-Bound $\bar{\delta}$ as a Function of v , p , q , and r



Similarly, the revenue of a high- or low-type seller using posted price with price z , in each of the four cases, is

$$\pi_H^H(B, z) = \begin{cases} z & \text{if } z \leq c, \\ (2r - r^2)z & \text{if } c < z \leq c + v, \\ 0 & \text{otherwise;} \end{cases}$$

$$\pi_H^L(B, z) = \begin{cases} (1 - (1-p)^2(1-r)^2)z & \text{if } v \leq c \text{ and } z \leq v, \\ (2p - p^2)z & \text{if } v \leq c \text{ and } v < z \leq c, \\ (2pr - p^2r^2)z & \text{if } v \leq c \text{ and } c < z \leq c + v, \\ (1 - (1-p)^2(1-r)^2)z & \text{if } v > c \text{ and } z \leq c, \\ (2r - r^2)z & \text{if } v > c \text{ and } c < z \leq v, \\ (2pr - p^2r^2)z & \text{if } v > c \text{ and } v < z \leq c + v, \\ 0 & \text{otherwise;} \end{cases}$$

$$\pi_L^H(B, z) = \begin{cases} (1 - p^2(1-r)^2)z & \text{if } v \leq c \text{ and } z \leq v, \\ (2(1-p) - (1-p)^2)z & \text{if } v \leq c \text{ and } v < z \leq c, \\ (2r(1-p) - r^2(1-p)^2)z & \text{if } v \leq c \text{ and } c < z \leq c + v, \\ (1 - p^2(1-r)^2)z & \text{if } v > c \text{ and } z \leq c, \\ (2r - r^2)z & \text{if } v > c \text{ and } c < z \leq v, \\ (2r(1-p) - r^2(1-p)^2)z & \text{if } v > c \text{ and } v < z \leq c + v, \\ 0 & \text{otherwise;} \end{cases}$$

$$\pi_L^L(B, z) = \begin{cases} (2r - r^2)z & \text{if } z \leq v, \\ 0 & \text{otherwise.} \end{cases}$$

PROOF OF PROPOSITION 3. We prove the proposition in three parts. In Part A we show that there is no separating

equilibrium in which the high-type seller uses posted price and the low-type seller uses auction. In part B we show that when $v \in [\nu_1, \nu_2]$, there exists a separating equilibrium in which the high-type seller uses auction and the low-type seller uses posted price v . Finally, in Part C we show that for $v \in (\nu_1, \nu_3)$, this is the only equilibrium that survives the intuitive criterion refinement.

Part A. Note that $\pi_L^L(A) < \pi_L^L(B, v)$, which means that conditioned on the type of sellers being revealed, the low-type seller always prefers posted price v to auction. Therefore, the low-type seller never uses an auction in a separating equilibrium.

Part B. Note that for a separating equilibrium in which the high-type seller uses auction and the low-type seller uses posted price to exist, the following two conditions are necessary and sufficient:

$$\pi_L^L(B, z) \leq \pi_L^H(A),$$

$$\pi_H^H(A) \geq \pi_H^L(B, z).$$

The first condition guarantees that the low-type seller cannot benefit from deviating, and the second condition guarantees that the high-type seller cannot benefit from deviating. $\pi_L^L(B, z)$ is optimized at $z = v$, and is equal to $(2r - r^2)v$. Having this less than or equal to $\pi_L^H(A)$, and using basic calculus, gives us the condition $v/c \geq \nu_1$. Similarly, solving the second inequality for v gives us condition $v/c \leq \nu_2$. If nonexpert buyers' beliefs are L for posted prices and H for auction, then $\nu_1 \leq v/c \leq \nu_2$ is also sufficient for existence of this equilibrium.

Part C. Finally, we show that if $v_1 \leq v/c \leq v_3$, the separating equilibrium in which the high-type seller uses auction and the low-type seller uses posted price is the only pure strategy separating Nash equilibrium that survives intuitive criterion refinement. Assume for sake of contradiction that there exists another separating equilibrium. We already know from Part A of this proof that the low-type seller cannot be using auction. Therefore, both types must be using posted price (with different prices) in this equilibrium. Using the same argument as in Part B of the proof, we know that the low-type seller must be using posted price v . Suppose that the high-type seller is using posted price ζ . For this to be a separating equilibrium, the low-type seller should not benefit from deviating and mimicking the high-type seller: $\pi_L^L(B, v) \geq \pi_L^H(B, \zeta)$. Using basic calculus, we can show that this implies the following condition on ζ . We must have $\zeta \leq ((r-2)v)/((p-1)(pr-r+2))$. Let $\pi^* = \pi_H^H(B, \zeta)$ be the profit of the high-type seller (in the hypothetical separating equilibrium) subject to this constraint.

If $\pi_H^H(A) > \pi^*$, then the high-type seller benefits from deviating to auction unless nonexperts' belief about auction is L . But note that if $v/c > v_1$, nonexperts' belief about auction cannot be L according to intuitive criterion refinement. Specifically, since the high-type seller benefits from deviating to auction and the low-type seller never benefits from deviating to auction even if buyers' belief in auction is H , according to the intuitive criterion refinement, buyers' belief in auction should be H . Therefore, if $\pi_H^H(A) > \pi^*$ the high-type seller benefits from deviating to auction and the hypothetical equilibrium cannot exist. Using basic calculus, the condition $\pi_H^H(A) > \pi^*$ reduces to $v/c \leq v_3$. Therefore, for $v/c \in (v_1, v_3)$, the separating equilibrium in which the high-type seller uses auction and the low-type seller uses posted price is the only pure strategy separating Nash equilibrium that survives the intuitive criterion refinement. \square

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