Electronic Commerce Research and Applications 9 (2010) 507–521

Contents lists available at ScienceDirect

Electronic Commerce Research and Applications

journal homepage: www.elsevier.com/locate/ecra

A meta-analysis on the effects of online auction design options: The moderating effect of value uncertainty ☆

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ARTICLE INFO

Article history:
Received 15 November 2008
Received in revised form 10 March 2010
Accepted 14 March 2010
Available online 18 March 2010

Keywords:
Online auction
Public reserve price
Secret reserve option
Buy-out option
Value uncertainty

ABSTRACT

Online auction design options (the public reserve price, secret reserve option and buy-out option) are critical in determining auction outcomes (the number of bids, the probability of sale and auction price). However, previous studies about the impacts of online auction design options on auction outcomes have generated inconsistent or even contradictory results. To synthesize the inconsistencies and reach more substantive conclusions, we conduct this meta-analysis study. Furthermore, to explain the inconsistencies, we identify the value uncertainty of auction items as a key moderator on the impacts of auction design options on auction outcomes, and verify the moderating effects using meta-analysis methods.

This study has three main findings: (i) the public reserve price has a positive effect on the auction price, and this effect is stronger when the value uncertainty of auction items is higher; (ii) the secret reserve option has a positive effect on the auction price when auction items are of low value uncertainty, but the magnitude of this effect decreases when the value uncertainty increases; (iii) the buy-out option has positive effects on both the probability of sale and the auction price when auction items are of low value uncertainty, but has negative effects on these two auction outcomes when auction items are of high value uncertainty.

1. Introduction

Online auction marketplaces are prevalent in contemporary electronic commerce (Li et al. 2008, Ockenfels et al. 2006). In online auctions, auction design options (the public reserve price, secret reserve option and buy-out option) are critical in influencing auction outcomes (the number of bids, the probability of sale and auction price) (Klemperer 1999). Many researchers have examined the effects of online auction design options on auction outcomes; however, they have generated inconsistent and even contradictory findings (Ockenfels et al. 2006). Based on a comprehensive survey of the literature, we find that the inconsistencies mainly exist in the following three types of relationships:

(i) The relationship between the public reserve price and the auction price: some researchers found that the public reserve price has a negative effect on the auction price (e.g. Bajari and Hortacsu 2003, Heyman et al. 2004), but some other researchers indicated that the effect is positive according to signaling and anchoring theories (e.g. Ariely et al. 2003).

(ii) The relationship between the secret reserve option and the auction price: several researchers found that the secret reserve option has a negative effect on the auction price (e.g. Dewally and Ederington 2006b, Katkar and Reiley 2006). However, some other researchers suggested that the effect is positive (e.g. Bajari and Hortacsu 2003).

(iii) The relationship between the buy-out option and auction outcomes: most researchers concluded that the buy-out option can increase the probability of sale and the auction price, especially when bidders are risk-averse (Chan et al. 2007, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004) or time impatient (Matthews 2004). However, some other researchers found that the buy-out option reduces auction efficiency and fails to increase the auction price (Peeters et al. 2007).

☆ This research is supported by RGC General Research Fund No. 9041194 (formerly known as Competitive Earmarked Research Grant) from the Hong Kong Government and CityU Strategic Research Grant No. 7001895.

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doi:10.1016/j.elerap.2010.03.003

Contradictions also exist among recommendations from practitioners. Take the relationship between the public reserve price and the auction price as an example. Kaiser and Kaiser, the authors of a famous eBay user guide book, *The Official eBay Guide to Buying, Selling, and Collecting Just about Anything*, suggested that sellers should set a low public reserve price and a high secret reserve price in the same auction, to "generate a lot of curiosity, which can translate into bids" (Katkar and Reiley 2006, p. 4). However, some sellers and bidders suggested that this type of auction (with a low public reserve price and a secret reserve option) wasted bidders' time and inhibited bidders' intention to bid (Katkar and Reiley 2006).

We try to synthesize and make sense of the inconsistent research findings in this study. In particular, two research questions are examined:

(1) What are the relationships between online auction design options and auction outcomes?
(2) What are the reasons for the contradictory findings on the relationships between online auction design options and auction outcomes?

To answer the first question, we survey the literature and summarize the theories on the relationships between online auction design options and auction outcomes. We also synthesize the existing research findings in the literature by meta-analysis methods. Meta-analysis can "correct disparities which arise from isolated investigations of individual experiments" and "reconcile outcomes of separate studies" (Montazemi and Wang 1988–89, p. 102). Therefore, our conclusions will be more substantive than the conclusions in the previous studies. The substantive conclusions may guide sellers in setting auction design options when they are pursuing better auction outcomes.

To address the second research question, the value uncertainty of auction items is identified as a key moderator on the relationships between online auction design options and auction outcomes. We verify the moderating effect by two meta-analysis methods. Our findings indicate that value uncertainty helps explain the majority of the inconsistencies. These findings offer useful guidelines to sellers: when the auction items are of different types, how should they set auction design options differently?

The rest of this paper is organized as follows: in the next section, we review auction design options and related theories, and propose our research hypotheses. Following this literature review section, we introduce our research methodology. Afterwards, we present our research results. Finally, we provide our conclusions including implications, limitations, and future research.

2. Literature review and hypotheses development

Online auction marketplaces have experienced an extremely rapid growth in recent years (Li et al. 2008, Ockenfels et al. 2006). For example, the most prevalent online auction marketplace, 'eBay', achieved 1340 times more annual net revenue in 2007 than a decade ago (US$ 7.67 billion in 2007 vs. US$ 5.7 million in 1997). In the second quarter of 2008, eBay had approximately 84.5 million active users, and these users posted 667 million listings on its online auction platform.

The dominant auction format in online auction marketplaces is the ascending-price auction (also called English auction) (Ockenfels et al. 2006). In this research, we focus on this ascending-price auction format. In the ascending-price auction, bidders overbid the existing highest bid until only one bidder remains, and then the auction item is sold to the remaining bidder at the highest bid. On eBay, a bidder can submit bids directly to overbid the current highest bid. The bidder also can submit a bid to a bid agent, which will automatically overbid the rivals by increasing the highest bid at a small increment, until the submitted bid is reached or all the rivals quit. It is worthwhile to note that, according to the standard auction models, a bidder's equilibrium strategy in an ascending-price auction is to bid his or her own valuation of the auction item (Menezes and Monteiro 2008). This property will be implicitly used in the following subsections.

2.1. Auction design options

Ockenfels et al. (2006) surveyed online auction literature and presented three important seller design options: (i) public reserve price, (ii) secret reserve option, and (iii) buy-out option. These three types of price-related online auction design options are widely used in online auction marketplaces.

The public reserve price is also called the *minimum bid*, *starting bid* or *opening bid*. It is the lowest bid that a bidder can submit in an auction. The public reserve price is observable to all the bidders in the auction. The secret reserve price is the minimum price below which the seller can choose not to sell the auction item. The amount of secret reserve price is not observable to bidders. Bidders are only informed whether there is a secret reserve price, and whether it has been met. The buy-out option, also called the *buy-it-now option*, *buy now option* or *buy option*, is an auction option commonly used in online auctions but rarely seen in conventional auctions (Ockenfels et al. 2006). The buy-out option allows bidders to directly purchase an auction item at a specified buy-out price. There are two types of buy-out options: (i) the temporary buy-out option, which is available only before the first bid is submitted, such as the 'Buy-It-Now' option on eBay, and (ii) the permanent buy-out option, which is available during the whole auction procedure, such as the 'Buy-price' option on Yahoo! (Gallien and Gupta 2007). In essence, the permanent buy-out option and the temporary buy-out option are similar, because both of them offer bidders a chance of direct purchase. The temporary buy-out option is more prevalent than the permanent buy-out option, in part because eBay uses the temporary buy-out option. In this paper, we focus on the temporary buy-out option.

2.2. Auction outcomes

Three types of auction outcomes are most frequently studied in online auction literature: (i) the number of bids, (ii) the probability of sale, and (iii) the auction price (Ockenfels et al. 2006).

The number of bids measures the number of bids or bidders involved in an auction (Baker and Song 2007). A bidder's entry in an auction depends on whether the perceived payoff of entry is more than the perceived cost (Jenamani et al. 2007). The bidder's perceived cost is the time and effort spent in the auction. The bidder's perceived payoff is determined by the achieved value when the bidder wins the auction and the chance of winning. The probability of sale is the probability that an auction ultimately ends in a sale (Gilkeson and Reynolds 2003). There are several reasons for auction failure: (i) an auction never attracts a bid; (ii) the public reserve bid is too high to be overbid by any bidder; or (iii) the secret reserve price of an auction is not reached. The auction price indicates the final closing price of an auction item (Baker and Song 2007), or the highest bid submitted in an auction (Dewally and Ederington 2006b, Wolf and Muhanna 2005). The auction price is an indicator of the price bidders are willing to pay in an auction.

2.3. Inconsistent findings and value uncertainty

The inconsistent findings about the relationships between auction design options and auction outcomes may be caused by two types of factors: (i) statistic errors in individual studies such as sampling error, measurement unreliability, type I and type II errors. (ii) the effect of moderators such as variables with regards to experiment settings and research context (Montazemi and Wang 1988–89). The statistic errors in individual studies can be corrected by synthesizing multiple studies via meta-analysis methods (Montazemi and Wang 1988–89). The effect of moderators also can be verified by meta-analysis methods (Sirmans et al. 2006, Stanley and Jarrell 2005), although these moderators should be theoretically derived (Montazemi and Wang 1988–89).

To search for moderators, it is worthwhile to analyze the reasons why auction design options impact auction outcomes. According to the literature (Klemperer 1999, Lucking-Reiley 2000, Ockenfels et al. 2006), we classify the impacts of auction design options on auction outcomes into three categories: (i) Online auction design options directly impact auction outcomes without changing bidders' valuations of auction items. For example, a high public reserve price can block bidders with low valuations of an auction item outside the auction, and thus decrease the number of bids (Ockenfels et al. 2006). (ii) Online auction design options impact auction outcomes by directly changing bidders' valuations of auction items. For example, online auction design options may be interpreted as value signals of an auction item, which may influence bidders' valuations of the auction item, and thus impact the auction price (Cai et al. 2007). (iii) The previous type of impacts may be amplified because bidders' valuations may be influenced by other bidders' bidding behavior. This influence can exist for at least two reasons. One reason is the observational learning effect: a bidder adjusts his or her willingness to pay (WTP) when other bidders increase bids on the auction item. Kauffman and Wood (2006) found that the same bidder is willing to pay higher when other bidders have expressed interest in the item, exhibiting a type of herd behavior. The other reason is auction fever (also called *competitive arousal*, *bidding frenzy*, *bidding war*), which is "an excited and competitive state-of-mind, in which the thrill of competing against other bidders increases a bidder's WTP in an auction, beyond what the bidder would be willing to pay in a posted-price setting" (Ockenfels et al. 2006, p. 23).

If bidders can accurately estimate the value of an auction item, auction design options are less likely to impact bidders' valuations of the auction item (Klemperer 1999, Milgrom and Weber 1982). In this situation, auction design options directly impact auction outcomes without changing bidders' valuations. This situation is close to the independent private value auction model, in which bidders' valuations are influenced only by their own value signals (Klemperer 1999, Milgrom and Weber 1982). However, if bidders are uncertain of their valuations of an auction item, their valuations are likely to be influenced by the value signals from auction design options and other bidders' bidding behavior. In this situation, auction design options may not only directly, but also indirectly impact auction outcomes by influencing bidders' valuations of the auction item. The indirect impacts can also be amplified by the influence of bidders' valuations on each other (Klemperer 1999, Milgrom and Weber 1982, Ockenfels et al. 2006). This situation is close to the common value auction model, in which each bidder's valuation may be influenced by all the value signals in the auction (Klemperer 1999, Milgrom and Weber 1982, Ockenfels et al. 2006).

In conclusion, the impacts of online auction design options on auction outcomes are different when bidders can or cannot accurately estimate the value of an auction item. We use the concept of "value uncertainty" to represent bidders' uncertainty on their valuations of an auction item.

Uncertainty is "the lack of complete certainty, that is, the existence of more than one possibility" (Hubbard 2007, p. 46). It also means "the 'true' outcome/state/result/value is not known" (Hubbard 2007, p. 46). Uncertainty is caused by imperfect information (Daft and Lengel 1986, Dimoka and Pavlou 2007), such as "the difference between the amount of information required to perform the task and the amount of information already possessed" (Galbraith 1977, p. 5). Based on this concept of uncertainty, we define value uncertainty as bidders' lack of complete certainty on their valuations of an auction item. In online auctions, there are two interrelated reasons for the value uncertainty (Dimoka and Pavlou 2007, Menezes and Monteiro 2008). One reason is that there is no clear sense of the market value of an auction item. For example, bidders are less likely to know how much a painting is worth before the auction ends. The other reason is an incomplete description of an auction item. For example, bidders cannot directly observe a rare coin in an online auction. They have to rely on the electronic cues (such as a text and pictures) which may not be sufficient, accurate, or even correct (Josang et al. 2007, Kauffman and Wood 2006, Manvi and Venkataram 2005). It is difficult for bidders to accurately estimate the value of the auction item based on imperfect information.

Bidders are less likely to accurately estimate the value of high value uncertainty auction items than low value uncertainty auction items. As we discussed above, we theorize that the effects of auction design options on auction outcomes are different when auction items are of low or high value uncertainty. In the following subsection, we develop hypotheses on the effect of each auction design option on each auction outcome, and compare the effects when auction items are of high or low value uncertainty.

2.4. Hypotheses development

2.4.1. Public reserve price and auction outcomes

A public reserve price is the lowest bid which bidders may submit. It will prevent the bidders with low WTPs from entering the auction. In an extreme situation, if a public reserve price is higher than the highest WTP of all the bidders, no bidder will bid on the item and the auction fails. Therefore, we hypothesize that the level of a public reserve price will negatively affect the number of bids and the probability of sale:

H1a: The level of a public reserve price has a negative effect on the number of bids in online auctions.
H1b: The level of a public reserve price has a negative effect on the probability of sale in online auctions.

As to the effect of the public reserve price on the auction price, there are both positive and negative impacts. On one hand, the positive impact is supported by at least three arguments. First, the public reserve price can extract profit from the winning bidder's surplus. If the public reserve price lies between the second highest WTP and the highest WTP, the winner has to pay more than the public reserve price, rather than the second highest WTP (Menezes and Monteiro 2008, Ockenfels et al. 2006). This effect is caused by the English auction format, thus is not influenced by value uncertainty of auction items. Second, the public reserve price serves as a signal of auction item value (Cai et al. 2007). The higher the item value signal there is, the higher bidders will be likely to pay (Cai et al. 2007). Third, the public reserve price also serves as an anchoring price. Bidders adjust their WTPs based on this anchor, even though the anchor may be not reasonable (Ariely et al. 2003, Beggs and Graddy 2009, Häubl and Leszczyc 2004, Tversky and Kahneman 1974). The effects in the second and third arguments are more likely to happen when auction items are of high value uncertainty. In contrast, when auction items are of low value uncertainty, bidders' valuations are mainly depended on private information and cannot be easily influenced by other signals such as the public reserve price.

On the other hand, some researchers proposed that a lower public reserve price may increase the auction price (Bajari and

Hortacsu 2003, Heyman et al. 2004, Lucking-Reiley 2000). A lower public reserve price can bring more bidders into an auction, and these additional bidders will help in amplifying the observational learning effect and auction fever effect, which in turn may increase the auction price (Bajari and Hortacsu 2003, Heyman et al. 2004, Lucking-Reiley 2000). As we discussed before, this observational learning effect and auction fever effect are more likely to happen when auction items are of high value uncertainty.

We summarize all these theoretical arguments in Table 1. When auction items are of low value uncertainty, the dominant effect of the public reserve price is extracting profit from the winning bidder's surplus. In this case, we predict a positive effect of the level of public reserve price on the auction price. When the auction items are of high value uncertainty, there are both positive and negative effects. The net effect of the public reserve price is an empirical question. However, since the public reserve price only blocks bidders with low WTP (who have relatively little chance to win the auction), its negative effect may be relatively weak. Therefore, we hypothesize that the net effect of the public reserve price on the auction price is positive

H1c: When auction items are of low value uncertainty, the level of a public reserve price has a positive effect on the auction price in online auctions.

H1d: When auction items are of high value uncertainty, the level of a public reserve price has a positive effect on the auction price in online auctions.

2.4.2. Secret reserve option and auction outcomes

Besides setting a publicly observable reserve price, a seller can also set a secret reserve price, below which he or she can choose not to sell the auction item. A secret reserve price may decrease a bidder's utility by increasing the expected cost of participating in an auction and decreasing the chance of winning the auction (compared with the same auction without a secret reserve price) (Ockenfels et al. 2006). Consider the following situation: a bidder has overbid all the other bidders, yet the secret reserve price has not been met. If the bidder chooses to continually increase the bid until the secret reserve price is met (this can be conducted automatically by a bid agent), the bidder pays more for the item; if the bidder chooses to quit the auction, the time and effort spent in the auction will be wasted without any payoff. Therefore, bidders, especially risk-averse bidders, may try to avoid auctions with a secret reserve. Katkar and Reiley (2006) have illustrated this situation in their paper. For example, user *bowerbird-oz* claimed "I usually hit the back button when I see a reserve auction, especially those which start at $2. Can't be bothered wasting my time" (Katkar and Reiley 2006, p. 6). Thus, we hypothesize that the secret reserve option negatively impacts the number of bids:

H2a: The secret reserve option has a negative effect on the number of bids in online auctions.

When a secret reserve price has not been overbid before the close of an auction, the auction is fail. Therefore, a secret reserve price negatively impacts the probability of sale (Menezes and Monteiro 2008). Furthermore, a secret reserve discourages bidders' entry into an auction (Katkar and Reiley 2006). When auction items are of high value uncertainty, the reduce of bidders may weaken the observational learning effect (Kauffman and Wood 2006) and auction fever effect (Ockenfels et al. 2006), thus may further decrease the probability of sale. Therefore, we hypothesize that a secret reserve option decreases the probability of auction success:

H2b: The secret reserve option has a negative effect on the probability of sale in online auctions.

As to the relationship between a secret reserve option and the auction price, there are both positive and negative predictions. On one hand, a secret reserve option extracts profit from the winning bidder's surplus (Bajari and Hortacsu 2003, Vincent 1995). In successful online auctions, when the second highest WTP is less than the secret reserve price, the auction price will be increased until the secret reserve price is reached. Even in failed online auctions, a bid agent will automatically increase the highest bid to the highest WTP. These effects exist no matter if auction items are of high or low value uncertainty. On the other hand, a secret reserve option discourages risk-averse bidders' entry (Katkar and Reiley 2006). The decrease in the number of bidders weakens the observational learning effect (Kauffman and Wood 2006) and auction fever effect (Ockenfels et al. 2006), and thus negatively influences the auction price. This negative impact is more likely to exist when auction items are of high value uncertainty (Kauffman and Wood 2006).

We summarize all these theoretical predictions in Table 2. When auction items are of low value uncertainty, the dominant effect of a secret reserve option is to extract profit from the surplus of the bidder with the highest WTP. Hence, the secret reserve option has a positive impact on the auction price when auction items are of low value uncertainty. When auction items are of high value uncertainty, there are both positive and negative effects. The net effect of the secret reserve option is an empirical question. Compared with the public reserve price, the secret reserve option may have a stronger negative effect because it discourages the entry of risk-averse bidders (who may have high WTP) rather than low WTP bidders; its positive effect is also weaker, because the secret reserve price is not observable, and thus cannot signal the value of the auction item or be an anchor. In summary, the secret

Table 1
Effects of public reserve price.

DV	Value uncertainty	Positive impact	Negative impact	Net impact and hypotheses
NBid	Both		• Block bidders of low initial WTP	H1a (−)
PSale	Both		• Additional condition for auction success	H1b (−)
APrice	Low	• Extract profit from the surplus of the winning bidder (Ockenfels et al. 2006)		H1c (+)
	High	• Extract profit from the surplus of the winning bidder (Ockenfels et al. 2006) • Signaling effect (Cai et al. 2007) • Anchoring effect (Ariely et al. 2003, Häubl and Leszczyc 2004, Tversky and Kahneman 1974)	• Block bidders of low initial WTP, weaken the observational learning effect and auction fever effect (Bajari and Hortacsu 2003, Heyman et al. 2004, Lucking-Reiley 2000)	H1d (+)*

NBid means the number of bids, *PSale* means the probability of sale, and *APrice* means auction price.
* The net effect is an empirical question. We temporarily hypothesize the relationship to facilitate this study.

Table 2
Effects of secret reserve option.

DV	Value uncertainty	Positive impact	Negative impact	Net impact and hypotheses
NBid	Both		• Discourage risk averse bidders' entry (Katkar and Reiley 2006)	H2a (−)
PSale	Both		• Additional condition for auction success	H2b (−)
APrice	Low	• Extract profit from the surplus of the winning bidder (Bajari and Hortacsu 2003, Vincent 1995)		H2c (+)
	High	• Extract profit from the surplus of the winning bidder (Bajari and Hortacsu 2003, Vincent 1995)	• Discourage risk averse bidders' entry, weaken the observational learning effect and auction fever effect (Katkar and Reiley 2006, Ockenfels et al. 2006)	H2d (−)*

NBid means the number of bids, *PSale* means the probability of sale, and *APrice* means auction price.
* The net effect is an empirical question. We temporarily hypothesize the relationship to facilitate this study.

reserve option has a stronger negative effect on the auction price when compared with the public reserve price. Therefore, we hypothesize a negative effect to facilitate our discussion.

H2c: When auction items are of low value uncertainty, the secret reserve option has a positive effect on the auction price in online auctions.
H2d: When auction items are of high value uncertainty, the secret reserve option has a negative effect on the auction price in online auctions.

2.4.3. Temporary buy-out option and auction outcomes

A temporary buy-out option offers a temporary opportunity for direct purchase. If a risk-neutral bidder's expected payoff of choosing the buy-out option is more than the expected payoff of participating in the auction, the bidder will choose the buy-out option. In this case, the auction becomes a pure posted-price sale. If no bidder takes the buy-out option and a bid has been submitted, the buy-out option disappears. In this case, the buy-out price works as a signal of the auction item value for bidders who have viewed the buy-out price.

When the buy-out option is executed, the number of bids is meaningless. Therefore, we only consider the impacts of the buy-out option on the probability of sale and the auction price. If the buy-out price is less than a bidder's WTP plus the perceived auction participation cost, the bidder is likely to purchase immediately. Therefore, sellers can transfer bidders' auction participation cost to their profit using the buy-out option. Researchers have conducted plenty of studies on this topic. The findings indicated that when bidders are risk-averse (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004) or time impatient (Gallien and Gupta 2007, Matthews 2004), they may choose to purchase directly, and the final price may increase. Moreover, when the buy-out price is higher than all the highest WTP, bidders can simply ignore the buy-out option and bid on the item. Therefore, a buy-out option will increase the probability of sale and the auction price.

However, there are also negative effects of the buy-out option. Peeters et al. found that the buy-out option may reduce auction efficiency, and at the same time fail to enhance revenue (Peeters et al. 2007). They explained that bidders treat the buy-out price as an anchor (the "roof"), and are reluctant to bid over the buy-out price (Peeters et al. 2007). From this perspective, a buy-out option may decrease bidders' WTP, and cause a lower probability of sale when there is a reserve price.

We summarize the effects of the buy-out option in Table 3. When auction items are of low value uncertainty, bidders' valuations are less likely to be influenced by the buy-out price and other bidders' behavior, thus the anchoring effect will be weak. In this case, the dominant effect of the buy-out option is to offer an opportunity for direct purchase and to extract profit from bidders'

Table 3
Effects of buy-out option.

DV	Value uncertainty	Positive impact	Negative impact	Net impact and hypotheses
PSale	Low	• Offer a chance of direct purchase, especially for risk averse sellers (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004)		H3a (+)
	High	• Offer a chance of direct purchase, especially for risk averse sellers (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004)	• Anchoring effect, as a ceiling of the highest bid, cause bidding reluctance (Peeters et al. 2007)	H3c (+)*
APrice	Low	• Extract profit from auction cost (Gallien and Gupta 2007, Matthews 2004) • Risk averse buyers will pay more (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004)		H3b (+)
	High	• Extract profit from auction cost (Gallien and Gupta 2007, Matthews 2004) • Risk averse buyers will pay more (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004) • Signaling effect	• Anchoring effect, as a ceiling of the highest bid (Peeters et al. 2007)	H3d (+)*

PSale means the probability of sale, and *APrice* means auction price.
* The net effect is an empirical question. We temporarily hypothesize the relationship to facilitate our study.

auction participation cost. Therefore, when auction items are of low value uncertainty, the buy-out option is more likely to have a positive effect:

H3a: When auction items are of low value uncertainty, the buy-out option has a positive effect on the probability of sale in online auctions.
H3b: When auction items are of low value uncertainty, the buy-out option has a positive effect on the auction price in online auctions.

When auction items are of high value uncertainty, bidders' valuations may be influenced by the buy-out price and other bidders' bids. Therefore, the buy-out option in this case may have both positive effects (extracting profit from bidders' participation cost and signaling effect) (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004) and a negative anchoring effect (Peeters et al. 2007). We hypothesize positive effects to facilitate our discussion, following the majority of existing research conclusions (Budish and Takeyama 2001, Chan et al. 2006, 2007; Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004),

H3c: When auction items are of high value uncertainty, the buy-out option has a positive effect on the probability of sale in online auctions.
H3d: When auction items are of high value uncertainty, the buy-out option has a positive effect on the auction price in online auctions.

3. Methodology

We used meta-analysis methods to synthesize the secondary data collected from published empirical studies to verify our hypotheses. The meta-analysis provides a systematic and comprehensive framework in which partially comparable empirical studies examining the relationships between similar variables can be combined and integrated (Capon et al. 1990). It surpasses qualitative and narrative literature reviews by offering more rigorous and substantive quantitative results (King and He 2006, Montazemi and Wang 1988–89).

3.1. Collection of source studies

Following the guidelines and suggestions by Hunter and Schmidt (1990) and Cooper (1998), we comprehensively collected all the available studies of the effects of auction design options. Available databases of journal papers, conference proceedings, working papers and PhD dissertations were included. The steps and criteria of data collection are illustrated in Appendix A. The four steps of data collection ensured the comprehensiveness of the source studies. The three eligibility criteria ensured that these studies rigorously satisfy our research purpose. Ultimately, 37 papers were identified as our source studies. Table 4 shows the distribution of these 37 papers. There are 22 journal articles, 3 conference papers, 10 working papers and 2 PhD dissertations. As illustrated in Table 4, the number of published journal papers and the total number of studies appear to have increased in recent years.

3.2. Coding

3.2.1. Datasets identification

Because some studies used multiple datasets to analyze the relationships between auction design options and auction outcomes, we identified and coded all these datasets. Appendix B illustrates a partial list of the datasets. In total, we have identified 80 datasets. Table 5 shows that the datasets from the source studies which cover multiple categories of auction items.

Table 4
Source studies.

	Journal papers	Conference proceedings	Working papers	PhD dissertations	Total
2001	1	1	2	0	4
2002	2	0	0	0	2
2003	3	0	0	0	3
2004	1	1	1	2	5
2005	3	0	2	0	5
2006	6	1	3	0	10
2007	6	0	1	0	7
2008	0	0	1	0	1
Total	22	3	10	2	37

Table 5
Auction items in datasets.

Categories	The number of datasets	Descriptions and sub-categories
Arts	2	Arts, such as paintings
Coins	28	Gold coins and silver coins
Collection	4	Comic books, stamps, baseball cards
Dolls	2	Beanie babies, Barbie dolls
Flatware	10	Sterling silver flatware
Board game	1	Board game
Gmail Invitations	3	Gmail invitations
Hardware	12	Computers, palms, iPod and MP3 players, computer accessories, digital cameras
Software	16	Software, DVD, CD, electronic game
Soft and hard	3	Mixture of software and hardware
Tickets	1	Tickets of matches
Others	1	Photography lenses
Not specified	3	Randomly collected auction data

3.2.2. Coding of value uncertainty

We coded the value uncertainty of auction items in the source studies in two rounds. In the preliminary round, we invited two experienced online auction users to classify the auction items into high or low value uncertainty groups. We listed all the auction items in our datasets, with a brief introduction of the item type, characteristics and state (e.g. new, used or refurbished). We asked the two raters to classify the auction items independently according to whether they can or cannot accurately estimate the value of the auction items based on the information collected before auctions. The initial rating resulted in 89.6% (69 out of 77) similarity between two raters (we cannot identify auction items in 3 datasets as either low value uncertainty or high value uncertainty, because the auction items in these datasets are a mix of multiple products). The high consistency between the two raters indicates an acceptable inter-rater reliability (Boudreau et al. 2001, James et al. 1984). All the inconsistencies were solved through a discussion with the authors. The classification results are illustrated in the 5th column of Appendix B.

The purpose of the second round is to get quantitative measures of the value uncertainty for the meta-regression analysis (see Section 3.3.2). In this round, we asked active online auction users to rate the extent to which they can accurately estimate the value of given auction items based on the information collected before auctions. The rating scale is from 1 (exactly) to 7 (not at all), with 4 as the middle rating of neither "exactly" nor "not at all". We invited 100 active online auction users to attend our coding procedure, and received 34 responses. All of the 34 respondents have bid in more than one auction in the year of 2008, and 56% of them have bid in more than three auctions. Out of these 34 respondents, 31 (91%) have an online auction experience of more than three years. The auction items they have bid on included items from multiple categories. The average ratings of value uncertainty are listed in the 6th column of Appendix B. We also classified the auction items as low or high value uncertainty items based on the average ratings. The median of average ratings is the average of 4.06 and 3.76, thus we used 4 as the frontier value.

The classification results in the two rounds are nearly the same. The only differences are caused by the choice of the frontier value. If we simply change the frontier from 4 to 4.07 in the second round, the classification results in the two rounds will be exactly the same. We used the classification results in the second round to conduct our data analysis.

The coding results are consistent with the definition of value uncertainty. For example, according to the definition, second hand items should have higher value uncertainty than brand new items. There are two reasons: the characteristics of second hand items cannot be described via electronic cues as easy as brand new items; online auction users can find the market value of brand new items (from parallel auctions and conventional marketplaces) much easier than second hand items. Our coding results also show that online auction users perceive higher value uncertainty for second hand items than similar brand new items.

3.2.3. Coding of auction option variables and auction outcome variables

According to the definitions and descriptions of variables in the source studies, we coded each auction option variable as one of the three types of auction design options, and coded each auction outcome variable as one of the three types of auction outcomes. For example, we coded the number of bids, the number of bidders and their natural logarithm transformation as "the number of bids". We coded the final closing price (Baker and Song 2007), the highest bid (Dewally and Ederington 2006b, Wolf and Muhanna 2005), WTP (Chan et al. 2007, Dewan and Hsu 2004, Melnik et al. 2005) and their transformations (e.g. the logarithm transformation, the sum with ship cost and division by market value) as "auction price". Two researchers independently coded all these variables. The coding results of these two researchers are exactly the same, which indicates a high inter-rater reliability (Boudreau et al. 2001, James et al. 1984).

3.3. Analysis methods

In general, effect sizes are calculated to synthesize the existing findings in meta-analysis studies (King and He 2006, Schepers and Wetzels 2007). However, in this study, the data collected from the source studies are multi-variable regression coefficients, and effect sizes computed by multi-variable regression coefficients cannot be meaningfully compared and combined (Lipsey and Wilson 2001). In other words, we cannot use effect-size based meta-analysis methods.

We used the sign test—a simple, robust and conservative nonparametrical meta-analysis method (Capon et al. 1990)—to synthesize the data we collected. The sign test is simply a binomial test, which can be used to synthesize research results even when the formats of results vary (Capon et al. 1990, Hedges and Olkin 1985, Hu et al. 2004). We also conducted a meta-regression analysis to complement the sign test. The meta-regression analysis is the regression analysis on the regression coefficients (Stanley and Jarrell 2005). It can be used to identify sources of variation among regression coefficients (Stanley and Jarrell 2005).

3.3.1. Sign test

We coded the research results from the source studies as four types of data points: (i) positive data points (including both significant and non-significant results), (ii) negative data points (also including both significant and non-significant results), (iii) significantly positive data points ($p < 0.05$), and (iv) significantly negative data points ($p < 0.05$).

There are two types of sign tests for synthesizing the research findings. The first type of sign test counts only significant results (Capon et al. 1990, Dochy et al. 2003). This method, however, fails to consider non-significant results with right directions (Bottomley and Holden 2001). The second type of sign test uses both significant and non-significant results. In this study, we conducted both types of sign tests to increase the accuracy and robustness of our findings.

3.3.2. Meta-regression analysis

We further conducted a meta-regression analysis to examine the moderating effect of value uncertainty on the relationships between auction design options and auction outcomes. Meta-regression analysis is "the regression analysis of regression analyses" (Stanley and Jarrell, 2005, p. 299). In meta-regression analysis, the regression coefficients in the source studies becomes the dependent variable, and the characteristics of datasets in the source studies becomes the independent variable (Sirmans et al. 2006). A detailed introduction of meta-regression can be found in Stanley and Jarrell (2005).

The meta-regression model adopted in this study is

$$\beta_j = \alpha_0 + \alpha_{1j}U_j + \varepsilon_j,$$

where $j = 1, 2, \ldots, N$ identifies each regression model, β_j is the regression coefficient for regression model j, U_j is the value uncertainty of the auction items related to regression model j, and ε_j is the residual error term. We are interested in the sign of α_{1j}. If α_{1j} is significantly positive, the moderating effect of value uncertainty will be positive. In contrast, if α_{1j} is significantly negative, the moderating effect of value uncertainty will be negative.

According to the meta-regression literature, the source studies involved in the meta-regression study are limited to those that have adopted linear regression models (Sirmans et al. 2006, Stanley and Jarrell 2005). We did not study the regression coefficients when the number of bids or the probability of sale is the dependent variable, because these regression models are nonlinear and thus not comparable (Sirmans et al. 2006, Stanley and Jarrell 2005). In other words, we only study the regression coefficients when auction price is the dependent variable. In this case, the regression coefficients (β_j) in the source studies may be influenced by the value level of auction items. Therefore, we included the value level of auction items as a control variable in an alternative model, to increase the accuracy of the meta-regression. The alternative model is

$$\beta_j = \alpha_0 + \alpha_{1j}U_j + \alpha_{2j}V_j + \varepsilon_j,$$

where V_j is the value level of auction items.

3.3.3. Robustness test

As we described in Section 3.2.1, some source studies used multiple datasets. In other words, one single study may have generated multiple regression coefficients on the same relationship based on multiple datasets or using different research models. In this study, we included all these data points in the sign tests and in the meta-regression analyses. To avoid the possible overweighed influence from one single source study or dataset,

Table 6
Sign test results.

IV	DV	Value uncertainty	Full data points				Significant data points only			
			Total	Pos	Neg	Sign test full	Total sig.	Pos Sig.	Neg sig.	Sign test sig.
PubResPrice	*NBid*		20	0	20	–	19	0	19	–
PubResPrice	*PSale*		22	0	22	–	22	0	22	–
PubResPrice	*APrice*		108	96	9	+	66	59	7	+
		Low	57	48	6	+	17	13	4	+
		High	51	48	3	+	49	46	3	+
SecretResOpt	*NBid*		13	0	13	–	12	0	12	–
SecretResOpt	*PSale*		21	1	20	–	21	1	20	–
SecretResOpt	*APrice*		66	38	26	n.s.	28	18	10	+
		Low	21	15	4	+	5	5	0	+
		High	45	23	22	n.s.	23	13	10	n.s.
BuyOutOpt	*PSale*		13	9	4	+	13	9	4	+
		Low	10	9	1	+	10	9	1	+
		High	3	0	3	N/A	3	0	3	N/A
BuyOutOpt	*APrice*		27	15	12	n.s.	22	14	8	n.s.
		Low	18	15	3	+	16	14	2	+
		High	9	0	9	–	6	0	6	–

PubResPrice means public reserve price, *SecretResOption* means secret reserve option, *BuyOutOpt* means buy-out option, *NBid* means the number of bids, *PSale* means the probability of sale, and *APrice* means auction price.
"+" indicates a significantly positive sign test result ($p < 0.05$), "–" indicates a significantly negative sign test result ($p < 0.05$), "n.s." indicates a non-significant result, and "N/A" indicates that the sign test is not applicable because of the limited data points.

we selected one representative regression coefficient with respect to each dataset or study, and conducted the sign tests and meta-regression analyses again using these "representative data points". The rules of data point selection can be found in Appendix C. If the research findings based on the "representative data points" can confirm the research findings based on all the data points, we can conclude there is robustness in our findings.

4. Results

The sign test results are illustrated in Table 6. As described before, we conducted two sign tests for each pair of independent and dependent variables. The sign test results based on all the data points (including both significant and non-significant results) are shown in the left panel, and the sign test results based only on significant data points are shown in the right panel. Since the two sign tests generate the same results (except in one case), we focus on the sign test results based on all the data points to facilitate the discussion.

The meta-regression analysis results are depicted in Table 7. The table also consists of two sets of meta-regression results: The first panel depicts the meta-regression results of the first model (the model without the control variable), while the second panel shows the meta-regression results of the second model (the model with the control variable). The two sets of results are consistent with each other. In the remaining part of the paper, we will explain our findings based on the meta-regression results of the second model (which should be more accurate with the control variable).

The first section of Table 6 (row 3–row 5) shows the effect of the public reserve price. We find that the existing research findings on the effect of the public reserve price on the number of bids are consistently negative (20 negative out of 20, sign test $p < 0.01$), and all the existing findings on the effect of the public reserve price on the probability of sale are also consistently negative (22 negative out of 22, sign test $p < 0.01$). Therefore, H1a and H1b are supported. On the contrary, we find the public reserve price has a statistically consistent positive effect on the auction price (96 positive out of 108, sign test $p < 0.01$). In other words, H1c and H1d are also supported. Furthermore, we have examined the moderating effect of value uncertainty on the relationship between the public reserve price and the auction price using the meta-regression analysis. The analysis results are shown in Table 7. We find that the effect of the public reserve price on the auction price is stronger (more positive) when value uncertainty is high ($\alpha_1 = 0.215$, $p < 0.01$). In other words, the public reserve price is more likely to induce a higher auction price when auction items are of higher value uncertainty.

The second section of Table 6 (row 6–row 10) illustrates our research results on the effects of the secret reserve option. We find that the secret reserve option has negative effects on the number of bids (13 negative out of 14, $p < 0.05$) and the probability of sale (20 negative out of 21, $p < 0.05$), thus H2a and H2b are supported. As to the relationship between the secret reserve option and the auction price, although the sign test based on the significant data points generate a positive result (18 positive out of 28, $p < 0.05$), the sign test based on all data points is insignificant (38 positive and 26 negative out of 66 data points). We divided the data points into two groups according to the value

Table 7
Meta-regression results.

IV	α_1	α_2	N	F	Adj. R^2
Model 1					
PubResPrice	0.210^{***}		107	94.507^{***}	0.466
SecretResOpt	-1.841^{***}		65	18.336^{***}	0.211
BuyOutOpt	-68.755^{***}		26	18.253^{***}	0.399
Model 2					
PubResPrice	0.215^{***}	0.010n.s.	108	47.118^{***}	0.451
SecretResOpt	-1.789^{***}	0.202n.s.	66	9.303^{***}	0.203
BuyOutOpt	-57.796^{***}	-17.862^{**}	27	13.380^{***}	0.488

$^{***}p < 0.01$, $^{**}p < 0.05$ (double-tailed).
The dependent variable is the regression coefficients of auction price in the literature. α_1 denotes the regression coefficient of auction items' value uncertainty. α_2 denotes the regression coefficient of auction items' value level, which is a control variable in this study.
PubResPrice means public reserve price, *SecretResOption* means secret reserve option, and *BuyOutOpt* means buy-out option.

Table 8
Summary of research findings.

		NBid		*PSale*		*APrice*	
		Hypothesis	Result	Hypothesis	Result	Hypothesis	Result
PubResPrice	Low	−(H1a)	√	−(H1b)	√	+(H1c)	√
	High					+(H1d)	√
SecretResOpt	Low	−(H2a)	√	−(H2b)	√	+(H2c)	√
	High					−(H2d)	n.s.
BuyOutOpt	Low			+(H3a)	√	+(H3b)	√
	High			+(H3c)	−(N/A)	+(H3d)	−

PubResPrice means public reserve price, *SecretResOption* means secret reserve option, *BuyOutOpt* means buy-out option, *NBid* means the number of bids, *PSale* means the probability of sale, and *APrice* means auction price.
"√" means the hypothesis is supported ($p < 0.05$). "n.s." means non-significance, i.e., the results in the source studies are statistically inconsistent. "N/A" means the data points are not enough to generate any statistical conclusion. "−" means the result shows a negative relationship.

uncertainty of auction items. The sign test results show a significantly positive relationship when auction items are of low value uncertainty (15 positive out of 21, $p < 0.05$), and a non-significant relationship when auction items are of high value uncertainty (23 positive and 22 negative out of 45 data points). Therefore, H2c is supported, but H2d is not supported. We further conducted a meta-regression analysis on the relationship between the secret reserve option and the auction price (Table 7, row 5), and find that the positive effect of the secret reserve option on the auction price is weaker when auction items are of high value uncertainty ($\alpha_1 = -1.789$, $p < 0.01$).

The third section of Table 6 (row 13 to row 18) illustrates our research results on the effects of the buy-out option. We find a significantly positive effect of the buy-out option on the probability of sale (9 positive out of 13, $p < 0.05$). However, when we divided the data points into two groups according to the value uncertainty of auction items, we find 9 out of 10 data points in the low value uncertainty group are positive, and all the 3 data points in the high value uncertainty group are negative. Therefore, H3a is supported (9 positive out of 10, $p < 0.05$). Although we cannot generate a strong conclusion on H3c based on only 3 data points, our result hints at a negative effect when auction items are of high value uncertainty. Row 16 shows a mixed relationship between the buy-out option and the auction price (15 positive and 12 negative out of 27). When we divide these data points into two subgroups, the low value uncertainty subgroup shows a significantly positive effect (15 positive out of 18, $p < 0.05$) and the high value uncertainty subgroup shows a significantly negative effect (9 negative out of 9, $p < 0.05$). Therefore, H3b is supported, but H3d is rejected. We also conduct a meta-regression analysis on the relationship between buy-out options and auction prices. We find that the moderating effect of value uncertainty is negative ($\alpha_1 = -51.796$, $p < 0.01$), i.e. the positive effect of the buy-out option on the auction price decreases as value uncertainty increases. This finding is consistent with the finding of the sign test. In other words, when auction items are of low value uncertainty, the effect of the buy-out option on the auction price is positive; however, when auction items are of high value uncertainty, the effect of the buy-out option on the auction price becomes negative.

We have also conducted the sign test and the meta-regression analysis based on the "representative" data points. The data analysis results are illustrated in Appendix C. Limited by the number of data points, the data analysis results may be not significant, but the signs of the results are consistent with the findings in Tables 6 and 7. This consistency shows the high robustness and reliability of our findings. The hypotheses and our results are summarized in Table 8.

5. Conclusions

This paper reconciles the inconsistent research findings on the effects of auction design options on auction outcomes. It also examines the reasons for the inconsistencies. Value uncertainty of auction items is identified and verified as a key driver of the inconsistent research findings. Using meta-analysis methods based on the secondary data collected from existing studies, this study generates several findings: (i) the public reserve price has a positive effect on the auction price, and this effect becomes stronger when the value uncertainty of auction items are higher; (ii) the secret reserve option has a positive effect on the auction price when auction items are of low value uncertainty, but the magnitude of this effect decreases as the value uncertainty increases; (iii) the buy-out option has positive effects on both the probability of sale and the auction price when auction items are of low value uncertainty, yet it has negative effects on both the probability of sale and the auction price when auction items are of high value uncertainty.

5.1. Theoretical contributions

To the best of our knowledge, this paper is the first quantitative review of the effects of auction design options on auction outcomes. It synthesizes the research findings in the literature and reaches more substantive research findings. Furthermore, this paper identifies value uncertainty as the key moderator and reconciles the apparent inconsistencies. There are three main contributions.

First, existing studies have generated contradictory findings on the effect of the public reserve price on the auction price (Ariely et al. 2003, Bajari and Hortacsu 2003, Heyman et al. 2004, Lucking-Reiley et al. 2007, Ockenfels et al. 2006). However, we find this effect is statistically positive. This finding highlights the positive effect of the public reserve price, such as extracting profit from buyers' surplus (Ockenfels et al. 2006), signaling effect (Cai et al. 2007) and anchoring effect (Ariely et al. 2003, Häubl and Leszczyc 2004, Tversky and Kahneman 1974). Moreover, we find that the positive effect of the public reserve price on the auction price is stronger when auction items are of higher value uncertainty. This finding implies that bidders are more likely to treat the public reserve price as a signal or an anchor of item value when auction items are of high value uncertainty. When practitioners and researchers propose that low public reserve prices can attract bidders and form a bidding war to increase seller profit (Bajari and Hortacsu 2003, Heyman et al. 2004, Lucking-Reiley 2000), our results suggest that these effects may be weak, or at least not dominant.

Second, while the existing findings on the effect of the secret reserve option on the auction price are also contradictory (Bajari and Hortacsu 2003, Dewally and Ederington 2006b, Katkar and Reiley 2006), we find that this effect is positive in the case of low value uncertainty items, and it decreases as the value uncertainty increases. However, we still have not reached a conclusion for items with high value uncertainty. Research suggests that the secret reserve option may increase the auction price when the auction is successful (i.e., when the secret reserve price is met) (Bajari and Hortacsu 2003, Ockenfels et al. 2006). Based on these suggestions, we further divided the data points in the high value uncertainty case into two groups: one group includes the data points of successful auctions, and the other group includes the remaining data points. We find that the secret reserve option has a statistically positive effect on the auction price when the auctions are successful (15 positive out of 18, $p < 0.05$), and has a consistently negative effect on the highest bid when unsuccessful auctions are included (15 negative out of 23, $p < 0.05$). These findings broaden our understandings about the secret reserve option. The secret reserve option may extract profit from bidders' surplus (positive effect), but it also can discourage risk-averse bidders' entry (negative effect) Katkar and Reiley 2006. In particular, when auction items are of high value uncertainty, the negative impact of the secret reserve option becomes stronger. In this case, the secret reserve option may decrease the highest bid and cause the auction to fail.

Third, we find that the buy-out option has positive effects on auction outcomes when auction items are of low value uncertainty, and negative effects when auction items are of high value uncertainty. In low value uncertainty auctions, bidders are certain about the value of auction items. In this case, sellers can directly sell auction items to bidders, particularly risk-averse or time-sensitive bidders, and transfer these bidders' auction cost to seller profit (Gallien and Gupta 2007, Matthews 2004). However, in high value uncertainty auctions, bidders are not certain about their valuations of auction items. They are less likely to directly purchase the auction items, and also less likely to bid over the buy-out price (especially when there are parallel auctions with similar items and similar buy-out price). In this case, the buy-out price works as the 'roof' on the auction price, and has negative effects on auction outcomes (Peeters et al. 2007). These findings indicate that the buy-out option may not be proper when auction items are of high value uncertainty.

5.2. Practical implications

Our findings also have several practical implications. For auctioneers, our research results offer several suggestions on how to set auction design options. First, in contrast to some researchers (Bajari and Hortacsu 2003, Heyman et al. 2004) and practitioners' (Katkar and Reiley 2006) suggestion to set a low public reserve price, our findings suggest that sellers should set a high public reserve price to get a high auction price. The reason is that a high public reserve price signals a high value of the auction item (Cai et al. 2007). Second, the existing suggestions from both researchers and practitioners on whether to set a secret reserve price are inconsistent. Based on our findings, when auction items are of low value uncertainty, sellers should use the secret reserve option to increase the auction price (Bajari and Hortacsu 2003, Vincent 1995). However, when auction items are of high value uncertainty, sellers should not use the secret reserve option. This is because the secret reserve option does not have the signaling effect, but may discourage the entry of risk-averse bidders (Katkar and Reiley 2006, Ockenfels et al. 2006). Third, although most of the researchers suggest that sellers should set a buy-out price (Budish and Takeyama 2001, Chan et al. 2006, Matthews and Katzman 2006, Reynolds and Wooders 2006, Tucker and Massad 2004), our findings suggest that sellers should set a buy-out price only when the auction items are of low value uncertainty. In contrast, when auction items are of high value uncertainty, sellers should not use the buy-out option, because the buy-out option has negative effects on auction outcomes.

For bidders in online auction marketplaces, this paper summarizes the effects of auction design options on auction outcomes, as well as the reasons for the effects. A better understanding of these effects can help buyers protect themselves from being influenced by sellers' strategic setting of auction design options, and also protect themselves from being influenced by other bidders' behavior. For example, when auction items are of high value uncertainty, bidders are likely to be influenced by the public reserve price and other bidders' bids. However, these value signals may have been distorted by sellers or by bidders' herding behavior (Ockenfels et al. 2006). A better understanding of the effects of these value signals may urge bidders to identify more objective value cues for their own benefit.

This study is also valuable for online auction companies. First, we find that the buy-out option has positive effects on auction outcomes in low value uncertainty auctions, but has negative effects in high value uncertainty auctions. These findings imply that retail pricing may be better than auctions when auction items are of low value uncertainty, because the cost of an auction may exceed the benefit generated from its price discovery process. Online auction marketplaces may want to offer sellers different transaction mechanisms based on the value uncertainty of each auction item. Second, when bidders perceive high value uncertainty of auction items, they may hesitate to submit their bids. To facilitate the auctions, perhaps online auction companies can implement IT mechanisms to provide information (for example, a Q&A section between sellers and bidders on each item description page) that decreases bidders' perceived value uncertainty.

5.3. Limitations

This study also has four main limitations. First, all the meta-analysis studies cannot avoid the "file drawer" (Rosenthal 1979) or "publication bias" (Scargle 2000) problem. A file drawer problem is a type of publication bias, which occurs when the publication of research results depends on their nature and direction (Dickersin 1990). In other words, when researchers are more likely to submit, or editors accept, positive rather than null (negative or inconclusive) results, studies of null results are lost "in the file drawer". This situation results in a publication bias (Rosenthal 1979, Scargle 2000). To reduce the "file drawer" or "publication bias" effect, we have carried out two remedies: (i) we included working papers and conference papers; (ii) we conducted sign tests and meta-regression tests using both significant and non-significant results. The results of sign test and meta-regression based on all the data points are consistent with the results based on only significant data points. This consistency indicates that the "file drawer" or "publication bias" problem is not serious.

Second, the data collected from source studies are restricted to eBay auctions, i.e. ascending-price auctions with temporary buy-out options. Caution should be exercised when generalizing our findings and applying them to other types of online auction marketplaces. However, since eBay is the most representative online auction website and its auction design options are similar to the auction design options on the other online auction websites, our results may be potentially generalized and applied to other online auction websites.

Third, limited by the data collected from the source studies, we cannot control for parallel auctions in the online marketplace. Parallel auctions of the same or similar auction items may influence the effects of auction design options on outcomes. For example, the buy-out option in parallel auctions may influence bidders' valuations of the auction items. However, notice that the auction items which have the same or similar auction items are usually of low value uncertainty (such as electronic products and books). For these types of auction items, the information revealed in the parallel auctions may also be revealed in other marketplaces (such as conventional marketplaces). In this case, the information revealed in the parallel auctions may be redundant for bidders. Since we have considered the information collected before auctions, we may infer that the influences of parallel auctions are limited in this study.

Fourth, the expertise of the online auction users on auction items in the second round of coding procedure may influence the coding results, which in turn may influence our research findings. To evaluate the influence of expertise, we also asked the online auction users to report their expertise on each type of auction items, and calculated the average expertise. We removed the datasets of auction items on which the average expertise is lower than 4, and conducted the sign tests again. This sign tests generate the same research findings. Therefore, we may conclude that the expertise of the online auction users is not a serious problem.

5.4. Future research

In this study, we identified value uncertainty as the key moderator of the relationships between auction design options and auction outcomes. Although value uncertainty explains the majority of inconsistencies, there may be other moderators. One possible moderator is that whether auction items are collection type or commodity type. Compared with commodity type auction items, bidders may enjoy more fun of competing for collection type items, and they may be more likely to ignore the buy-out option of collection type items. Further studies may investigate more moderators on the relationships between auction design options and auction outcomes.

We separately examined the effects of auction design options on three auction outcome variables in this study. However, auction success is simultaneously determined by all these three variables. Increasing only one of them and abandoning the others will not increase seller revenue sufficiently. For example, an extremely low buy-out price can cause 100% probability of sale, but it also sharply reduces the seller's revenue. We suggest future research that combines these three auction outcome variables as an integrated variable (e.g. expected seller revenue), and examine the effects of auction design options.

Another possible future research direction is to estimate the most profitable level of reserve price and buy-out price in online auctions (e.g. Paarsch 1997). Since value uncertainty moderates the effect of auction design options, it may influence the optimal level of reserve price and buy-out price. Future research may estimate the optimal level of reserve price and buy-out price whilst considering the value uncertainty of auction items. Moreover, future studies may also consider bidders' behaviors with regards to these two auction design options. For example, will the bidders' behavior change after the secret reserve price is met?

Future research can also examine the effects of combining of different auction design options. Some researchers have recommended a combination of the low public reserve price and the high secret reserve price. We find that this combination may decrease the auction price, especially when the auction items are of high value uncertainty. Future research can re-examine the effect of this combination carefully. Another interesting combination is the combination of buy-out option and secret reserve option. We find that the buy-out option works as a signal or anchor when it is not executed. If sellers set a high buy-out price and at the same time a low secret reserve price, it will be interesting to identify the effect of this combination.

Appendix A. Source study collecting and eligibility criteria

Based on the guidelines and suggestions by Hunter and Schmidt (1990) and Cooper (1998), we used the following methods to search and identify source studies (from all the available studies before May 2008) for our meta-analysis.

A.1. Journal papers

We searched all the computerized academic databases available at the City University of Hong Kong and the University of Science and Technology of China. These databases include EBSCO, ScienceDirect, Sage Journals Online, ProQuest, JSTOR, Wiley InterScience, SpringerLink, Emerand Fulltext, Project Muse and China Academic Journals Full-text Database. The keywords used in the search including "online auction", "internet auction", "eBay", "minimum bid", "reserve price", "buy-out" and "buy it now".

A.2. PhD dissertations

We also searched ProQuest PhD dissertation database using the same keywords used above. Through this method, two dissertations were identified as our meta-analysis source studies (actually, we found four dissertations, out of which two have correspondent published journal papers. These two dissertations were eliminated to avoid redundancy).

A.3. Conference proceedings

As our focus was on the IS perspective, we also searched IS international conference proceedings from the website "http://aisel.isworld.org/search.asp". As the website listed on the web page, ACIS (2002–2005), AMCIS (1995–2007), BLED (2001–2005), ECIS (2000–2005), ICIS (1980–2007), MCIS (2006–2007), MWAIS (2006–2007) and PACIS (1993–2005) were covered.

A.4. Working papers and complementary searching results

We also searched relevant working papers through three websites: "http://ideas.repec.org/", "http://www.ssrn.com/" and "http://www.nber.org/papers/". Google Scholar, i.e. "http://scholar.google.com", was also used to complement our search results. Furthermore, references which are potentially related to online auctions in several review papers (Bajari and Hortacsu 2004, Baker and Song 2007, Lucking-Reiley 2000, Ockenfels et al. 2006) and in these aforementioned source papers were also traced.

After we collected our source papers, we selected papers according to the following eligibility criteria:

(i) the focus of this paper is on online auction;
(ii) the study used data collected from actual auctions on eBay (could be either field experiment or field data);
(iii) the paper clearly reported at least one of the relationships in our hypotheses.

Appendix B. Datasets in source studies

References	Year	Number of observations	Average price	Type of value uncertainty[b]	Value uncertainty[c]	Items
Ahlee et al. (2005), Lee et al. (2006)	2004	141	131.9	Low	3.47	A board game called "Cashflow 101"
Ariely et al. (2003)	1999	275	N/A	Low	3.35	Tickets of the 2000 Rose Bowl game
Bajari and Hortacsu (2003)	1998	407	50.1	High	6.09	Mint and proof sets of US coins
Depken et al. (2008)	2007	192	471.23	Low	2.41	Brand new 8gb iPhone unlocked
Dewally and Ederington (2006a)	2001	3664	357	Low	4.06	30 Silver Age comic books
Dewally and Ederington (2006b)	2001–2002	5275	390	Low	4.06	Silver Age comic books
Dewan et al. (2001)	2000	807	36.86	High	4.82	"Mint never hinged" (MNH) stamps
Dewan and Hsu (2004)	2001	9981	33.07	High	4.82	"Mint never hinged" (MNH) stamps
Elfenbein et al. (2002)	2006	2437	88.23	Low	2.41	Consumer electronics, cameras and photography equipment, DVDs, computer equipment, and gift certificates
Gilkeson and Reynolds (2003)[a]	1999–2001	2628	24	High	5.29	Sterling silver flatware, specifically four different piece types-cold meat forks, gravy ladles, sugar shells, and teaspoons
Highfall and O'Brien (2007)[a]	2005	302	599.79	High	5.91	Arts (such as paintings)
Hou (2007)	2004	509	138.13	Low	3.04	CPU (Intel Pentium 4 2.4–3.0 GHz), both new and used
Kalyanam et al. (2001)	2000	564	262.34	Low	3.76	Palm Pilot
Kauffman and Wood (2005)	2001	919	31.03	High	6.09	Rare Coins
Kauffman and Wood (2006)	1999–2002	750	N/A	High	6.09	Coins minted in the US in the 19th century
Lei (2005)[a]	2004	54701	7.29	High	4.55	Gmail invitations
Livingston (2005)	2000–2001	861	409.96	High	4.76	Taylor Made Firesole irons (a variety of golf clubs)
Lucking-Reiley et al. (2007)	1999	461	173.2	High	6.09	US Cents
McDonald and Slawson (2002)	1998	460	263.1	Low	3.26	Collector-quality first-edition Harley-Davidson Barbie dolls
Melnik and Alm (2002)	2000	450	32.727	High	5.50	US 1999 $5 gold coin
Melnik et al. (2005)	2002	3828	93.39	High	6.15	US Morgan silver dollar coins in "Almost Uncirculated" (AU) condition
Nikitkov (2006)	2003–2004	462	1203.59	Low	3.76	Items in Consumer Electronics and Computers and Networking categories, for auction
Nikitkov (2006)	2003–2004	385	1203.59	Low	3.76	Items in Consumer Electronics and Computers and Networking categories, for posted price
Ruiz (2004)	2002	354	23.63	Low	2.88	Video game for playstation II: Virtua Fighter IV, New
Ruiz (2004)	2002	264	21.98	Low	3.76	Video game for playstation II: Virtua Fighter IV, Used
Simonsohn and Ariely (2006)	2002	8333	15	Low	2.88	DVD Movies, 54 movie titles

Appendix B (*continued*)

References	Year	Number of observations	Average price	Type of value uncertainty[b]	Value uncertainty[c]	Items
Song and Baker (2007)	2005	378	5.34	Low	2.88	Brand new DVD Movies
Song and Baker (2007)	2005	412	169.35	Low	2.41	Brand new MP3 players
Standifird (2001)	2000	102	349.99	Low	3.04	3 Com Palm Pilot vs.
Steckbeck (2004)	2000–2001	251	935.65	High	5.21	Hasselblad "C" type lenses
Wan and Teo (2001) [a]	2000	295	N/A	High	5.50	1909–1964 regular strikes, uncirculated, MS60–MS68, Lincoln coins
Wan and Teo (2001) [a]	2000	556	N/A	High	6.09	1909–1964 regular strikes Lincoln coins
Wan and Teo (2001) [a]	2000	379	N/A	High	6.09	1913–1938 regular strikes buffalo nickel coins
Yoo et al. (2006) [a]	N/A	432	N/A	Low	3.08	Digital cameras
Zhang and Trust-buildin (2004)	2004	135	283.13	Low	2.41	Three models of iPod by Apple
Zhang (2006) [a]	2004	1768	288.68	Low	2.41	15G and 20G Apple iPod Mp3

[a] Sub-datasets of the marked dataset were omitted in this table.
[b] The preliminary classification of "value uncertainty" is conducted by two experienced online auction users.
[c] The "value uncertainty" is the average of 34 online auction users' ratings on the extent to which they can estimate the value of auction items before auctions.

Appendix C. Robustness tests

C.1. Rules of representative data points selection

Some source studies has generated multiple regression coefficients on the same relationship based on multiple datasets or using different research models. In this research, we included all these data points in the sign tests and the meta-regression analysis. To avoid the possible overweighed influence from one single source study or dataset, we selected one representative regression coefficient with respect to each dataset or study, and conducted the sign tests and meta-regression analyses again using these "representative data points". The rules of representative data point selection are as follows:

(i) If the same dataset was used in several papers (the research models are different), we choose the paper follows the priority sequence: journal papers > conference proceedings > PhD dissertations > working papers. For example, we choose (Ba and Pavlou 2002) and omit (Pavlou and Ba 2000).

(ii) If one dataset was used in a paper and its sub-datasets were used in another paper, we choose the paper with the entire dataset. For example, we choose (Dewally and Ederington 2006b) rather than (Dewally and Ederington 2006a).

(iii) If multiple models based on the same dataset were presented in one study, we choose the full model. For examples, we choose the full model in Dewally and Ederington (2006b) and Lee et al. (2006).

(iv) If regression results based on a dataset and its sub-datasets were separately presented in a study, we choose the regression results based on the entire dataset to prevent the overweighed influence from one single author. For examples, we choose the regression results based on the entire dataset in Ba and Pavlou (2002), Dewan et al. (2001), Eaton (2005), and Gilkeson and Reynolds (2003).

C.2. Sign test results based on the representative data points

IV	DV	Total	Pos	Neg	Sign test	Total sig.	Pos sig.	Neg sig.	Sign test sig.
PubResPrice	*NBid*	4	0	4	N/A	4	0	4	N/A
PubResPrice	*PSale*	4	0	4	N/A	4	0	4	N/A
PubResPrice	*APrice*	16	13	3	+	13	11	2	+
SecretResOpt	*NBid*	5	0	5	–	5	0	5	–
SecretResOpt	*PSale*	7	0	7	–	7	0	7	–
SecretResOpt	*APrice*	13	7	6	n.s.	6	4	2	n.s.
BuyOutOpt	*PSale*	2	1	1	N/A	2	1	1	N/A
BuyOutOpt	*APrice*	6	3	3	n.s.	5	3	2	n.s.

PubResPrice means public reserve price, *SecretResOption* means secret reserve option, *BuyOutOpt* means buy-out option, *NBid* means the number of bids, *PSale* means the probability of sale, and *APrice* means auction price.

"+" indicates a significantly positive sign test result ($p < 0.05$), "–" indicates a significantly negative sign test result ($p < 0.05$), "n.s." indicates non-significant results, and "N/A" indicates that the sign test is not applicable because of limited data points.

Notice that we do not have enough data points to conduct all the sign tests as in Table 6.

C.3. Meta-regression results based on the representative data points

IV	α_1	N	F	Adj. R^2
PubResPrice	0.122*	15	3.527*	0.144
SecretResOpt	−0.679n.s.	12	0.531n.s.	−0.041
BuyOutOpt	−49.64*	5	6.48*	0.523

*$p < 0.1$ (double-tailed).

The dependent variable is the regression coefficients of auction price in the literature. α_1 denotes the regression coefficient of the value uncertainty of auction items.

PubResPrice means public reserve price, *SecretResOption* means secret reserve option, and *BuyOutOpt* means buy-out option.

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