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SEARCH COSTS AND EQUILIBRIUM PRICE DISPERSION IN AUCTION MARKETS

by

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Abstract

A leading explanation for price dispersion in posted-price markets is search costs. We incorporate this insight into a model of competing second-price auctions similar to eBay. By doing so, we extend the narrow literature on competing auctions to capture price dispersion, and grow the already vast literature on price dispersion to include auctions. We provide evidence for the model using data collected from eBay, identifying search costs by exploiting a discontinuity in the visibility of auctions due to eBay's search tool.

1. INTRODUCTION

Price dispersion in markets with multiple sellers is ubiquitous, and search costs, which cause some buyers to be unaware of some sellers, is a leading explanation. For example, in the theoretical work in Stahl (1989), sellers randomize between targeting unaware buyers by charging high prices and targeting all buyers by charging low prices. Empirical work supports an important role for search costs.¹

While there is a vast literature on price dispersion in posted-price markets, there has been little work in auction markets.² Yet auction markets exhibit significant price dispersion as well. For example, Table 1 shows the mean price difference within matched pairs of simultaneous auctions for the same new movie-DVDs on eBay (we describe the data later). Einav, Kuchler, Levin, and Sundaresen (2013) find price dispersion for a much wider range of eBay auctions.

Our goal is to grow the nascent literature on competing-auction markets to capture price dispersion and conversely to expand the price-dispersion literature to include competing-auctions markets. We establish theoretically that equilibrium price dispersion may exist in competing-auctions markets due to the same important explanation as in posted-price markets, search costs. Our modeling approach is to introduce search costs into a well-understood model of competing frictionless auctions in Peters and Severinov (2006). We then provide empirical support for the model, and ultimately for the importance of search costs in competing-auctions markets, using

¹ See Baye, Morgan, and Scholten (2006) for a detailed review of the price dispersion literature. The literature is vast, but some key theory papers include Stigler (1961), Diamond (1971), Salop and Stiglitz (1977), Reinganum (1979), Carlson and McAfee (1983), and Spulber (1995), which find price dispersion in pure strategies; and Rosenthal (1980), Varian (1980), Burdett and Judd (1983), Narasimhan (1988), Stahl (1989), and Baye and Morgan (2001), which find price dispersion in mixed strategies. Sorensen (2000) is one paper providing empirical support for search costs in an offline market. Brynjolfsson and Smith (2000), Scott Morton, Zettelmeyer, and Silva-Risso (2001), and Brown and Goolsbee (2002) are early empirically studies on the Internet and price dispersion.

² We are aware of only Chiou and Pate (2010) and Einav, Kuchler, Levin, and Sundaresen (2013), which report estimates of price dispersion among eBay auctions for gift cards and across a wide range of products, respectively.

data from eBay. eBay is the largest consumer auction platform in the world, and the primary auction format is a modified second-price auction.

Basic differences in the price-setting processes between auction markets and posted-price markets call for distinct analyses. For example, consider a market with simultaneous ascending second-price auctions, which has high search costs that cause buyers to be aware of only one auction each. In this case, the distribution of prices is equal to the distribution of the second-highest valuation of bidders across auctions (assuming at least two bidders per auction), and hence price dispersion occurs. In contrast, in the standard posted-price setting, when buyers are aware of only one seller each, sellers typically cannot price discriminate and a uniform monopoly price may occur.³ Hence, price dispersion would be absent or would have to come from another mechanism such as heterogeneous seller costs.⁴

Peters and Severinov (2006) construct a model of simultaneous modified second-price auctions that is similar to the eBay auction setting. In their model, all buyers are aware of all auctions and may bid as often as they would like and move between auctions. In this sequential bidding game, Peters and Severinov (2006) identify an equilibrium where all completed auctions have the same price, thereby establishing the auction analogue of the law of one price.⁵

To this model, we add search costs as in Varian (1980) and others, which are costs incurred by buyers to identify all available sellers. We model search costs as heterogeneous

³ Borenstein and Rose (1994) examine a posted-price market where sellers can price discriminate, the airline industry, which facilitates price dispersion.

⁴ In Stahl (1989), this limiting case leads all (posted-price) sellers to post the single-firm monopoly price. In the opposite limiting case, where all buyers are aware of all sellers, there are uniform prices for both auctions and posted-prices under standard assumptions and common production costs (e.g., the Peters and Severinov 2006 model for auctions and Bertrand competition for posted-prices). With intermediate levels of search costs, where some buyers are aware of some sellers, auctions versus posted-prices may have intermediate but distinct results.

⁵ As Peters and Severinov (2006) note, it is not a dominant strategy for buyers to immediately bid their valuations in the multi-auction setting, unlike in the single-auction setting (for intuition, see p. 225-226 of their paper).

across buyers and potentially correlated with buyer valuations.⁶ Buyers with low search costs conduct broad searches and identify all available auctions – these are the aware buyers. Buyers with high search costs conduct narrow searches and identify only a subset of the available auctions – these are the unaware buyers. In practice, in auction markets such as eBay, there are often dozens or hundreds of concurrent auctions for the same item. Search costs may arise in the form of the time and effort required to identify the set of potentially relevant listings, and to read all the listing titles and bodies to learn shipping method and other secondary item attributes.

We show that there exists an ex post equilibrium of the sequential bidding game using strategies that mirror those in Peters and Severinov (2006). However, when we add a first-stage in which buyers choose whether to search broadly or not, the results diverge substantially from the uniform price prediction of their model. We find that for any perfect Bayesian equilibrium of the full game, the expected ending price for auctions visible only to the aware buyers is below that for auctions visible to all buyers. Previous models of competing-auctions markets could mechanically generate price dispersion because buyers participate in only one auction each, and so the distribution over second-highest valuations determines prices. But this outcome is predicated on an extreme case of search frictions that permits no cross-auction awareness. Ours is the first that we are aware of that generates price dispersion in the more realistic scenario of varying auction visibilities, endogenous search decisions, and cross-auction bidding.

In the second part of the paper, we provide evidence for the model and the important role of search costs in competing-auctions markets. We examine data on eBay auctions for new movie-DVDs. The data contain information about the auctions' visibilities to buyers and hence about the search costs that buyers may incur to discover the auctions. eBay's search results are

⁶ A recent literature aims to structurally estimate the distribution over search costs, including Hong and Shum (2006), Moraga-Gonzalez and Wildenbeest (2008), De los Santos (2012), and Moraga-Gonzalez, Sandor, and Wildenbeest (2013), who find that search costs and search intensity across buyers are widely distributed.

quite sensitive to which search terms are used by the buyer. This sensitivity is due to eBay's default search algorithm, which generally requires every word in the search string to appear in the listing title for the listing to appear in search results. For example, listings for the movie DVD of *Batman Begins*, which was released in theaters in 2005 and on DVD in 2006, appear in the data with listing titles such as: "Batman Begins (2005)," "Batman Begins (2006)," and "Batman Begins." Consequently, buyers using the search string "Batman Begins 2005," "Batman Begins 2006," or "Batman Begins" would discover the first set, the second set, or all three sets of listings, respectively. Using the more inclusive "Batman Begins," however, requires the buyer to sort through many more listings.⁷ Therefore, when there are multiple listings for a product with different wording, then different buyers may discover different sets of listings. Generally, listings with more words, or more common words, are more visible.

We first test whether listings with more words are more likely to result in sale. This could be considered the starker form of price dispersion, indicating a difference of no sale versus a sale at a positive price. We find strong evidence of this relationship. For example, including the word "new" in the title of a new-DVD listing increases the probability of sale by 3.5 percent ($p=.03$). We then limit the sample to auctions that resulted in sale, and estimate the relationship between listing-title wording and the number of bidders in the auction. We again find a strong positive relationship, which is evidence that listings with more words are visible to more buyers. Finally, we test whether listings with titles with more words have higher prices. Indeed, this occurs. For example, having "new" in the listing title increases the ending price by 80¢ ($p<.01$).⁸

⁷ On July 5, 2013, "Batman Begins (2005)" returned 126 auctions, "Batman Begins (2006)" returned 10 auctions, and "Batman Begins" returned 332 auctions.

⁸ Schneider (2013) analyzes the effect of wording differences on price differences between auction and posted-price "BIN" listings on eBay. Auction price are more likely to exceed BIN prices when auctions contain extra words.

To our knowledge, this is the first study to explicitly examine the connection between search costs and price dispersion in auctions. A notable aspect of our analysis is that we directly observe the friction – a wording difference – and its effect on price. It is also contributes to the growing literature on competing auctions. As noted in Peters and Severinov (2006), the observed behavior in online auctions often deviates significantly from single-auction-setting predictions, and hence there is a need for work in this area. Very interesting related studies include Haruvy and Popkowski (2010), who show empirically that price dispersion decreases when bidders are given explicit incentives to monitor competing auctions, and Anwar, McMillan, and Zheng (2006) who show that auctions won by buyers who bid across multiple simultaneous auctions have lower prices. We note that the lower prices are a prediction of aware bidding that arises directly from our model.⁹

In Section 2 of this article, we provide the model; in Section 3, we describe the data and the eBay setting; Section 4 contains the empirical analysis; and Section 5 concludes.

2. PRICE DISPERSION IN AUCTION MARKETS WITH SEARCH FRICTIONS

In real-world consumer auction markets, buyers participate in multiple simultaneous auctions for the same item in their search the best price (e.g., see Anwar, McMillan, and Zhang 2006). This behavior is a challenge for much empirical work on auctions because it invalidates a key identification condition that high bids can be treated as independent draws from the distribution of an order statistic.¹⁰ If all buyers participate in all auctions, then the game is

⁹ Surveys of the Internet auctions literature include Bajari and Hortacsu (2004), Ockenfels, Reiley, Sadrieh (2006), and Hasker and Sickles (2010). Other theoretical studies of multi-auction settings include Hendricks, Onur, and Wiseman (2012), who investigate bidding strategies in sequential auctions; and Wolinsky (1988), McAfee (1993), Peters and Severinov (1997), and Virág (2010), who examine simultaneous-auction settings but with different focuses (e.g., buyers may participate in only one auction, which is less suitable for studying price dispersion).

¹⁰ See Athey and Haile (2002) and Song (2004) for more. See Adams and Zeithammer (2010) for more discussion of the limitations of the sealed-bid abstraction.

equivalent to a single multi-unit *Ausubel auction*, as Peters and Severinov (2006) demonstrate in their model of cross-bidding.¹¹ Importantly, this suggests that the price dispersion that would be predicted by the canonical model of second-price auctions, which comes from the variance of the second-order statistic of draws from the distribution of valuations, is an artifact of the assumption that buyers participate in only one auction each, an extremal case of search frictions.

We propose an alternative model of price dispersion in second-price auctions. We adopt the framework of Peters and Severinov (2006) as a starting point – a *worst-case* in the sense that it predicts perfect price equality – and show how adding search frictions generates a robust and economically meaningful explanation for price dispersion. Ours is the first model that we are aware of that generates price dispersion in an auction platform where buyer search and participation decisions are endogenous, and grows the young literature on competing auctions.

Sellers compete by listing auctions on a common platform. The auctions proceed simultaneously and buyers can participate in multiple auctions. Consistent with the variability of experience and expertise among sellers in real-world two-sided markets, auctions are exogenously either “high visibility” or “low visibility.”¹² All buyers are aware of the former; in the first stage of the game, buyers may also incur search costs in order to discover and participate in the latter. The second stage of the game is the bidding phase. In this second stage, we extend the equilibrium of Peters and Severinov (2006) in two ways: (1) we demonstrate that it is an equilibrium *ex post*, which obviates the need to specify beliefs, reasonable or otherwise; and (2)

¹¹ The Ausubel auction is an open multi-unit ascending auction format that delivers a uniform price at which the quantity demanded is equal to the quantity supplied. See Ausubel (2006) and Krishna (2010).

¹² It would not be difficult to weaken the assumption of exogenous seller types and describe a first-stage game in which sellers with idiosyncratic learning costs choose either to learn and post a high-visibility auction, or not to and post a low-visibility one. This would not substantively change our results, but more importantly it would not add dramatically to the realism of the model, which is why we omit it. Once learned, techniques for improving the visibility of an auction are virtually costless, and therefore we believe that the heterogeneity of auction visibility, as documented in the empirical section of our paper, represents behavior in a much larger game over a longer period of time than a single auction.

we incorporate the possibility of low-visibility auctions and non-searching buyers whose presence was determined endogenously in the first stage.

The model is not identical to the eBay setting. For example, in the model, the ending times of the competing auctions are identical, while on eBay these times may be somewhat staggered (though we attempt to control for this in our empirical analysis by examining auctions with close end times). The objective of the model is not necessarily to model precisely the eBay setting, but to establish how search costs may generate equilibrium price dispersion in a setting with competing auctions, of which eBay is a notable example. It seems reasonable that the intuition from the model would extend to many similar settings.

We begin by introducing primitives of the model. Then we solve the game by backwards induction. This involves first solving the bidding subgame by extending the sequential bidding solution of Peters and Severinov (2006) to a setting in which a subset of buyers are aware of only a subset of the available auctions. Using the outcome of the bidding subgame, we solve for the first-stage search decisions of buyers. Finally, we show that any perfect Bayesian equilibrium of the full game exhibits price dispersion, a prediction that we take to the data in Section 4.

A) Model primitives

There are two auctions and $n > 2$ buyers in a market for a homogenous good. Each auction has a starting price of zero.¹³ Buyer valuations are distributed *i.i.d.* according to a discrete distribution $F(v)$ on a grid $V = \{\underline{v}, \underline{v} + d, \underline{v} + 2d, \dots, \underline{v} - d, \bar{v}\}$, with $0 < \underline{v} < \bar{v}$,

¹³ In reality, buyers may set a minimum or a public reserve price. Here we normalize the reserve of both auctions to zero and omit the question of optimal reserves.

and a constant grid step d . A buyer i with valuation v_i who obtains a single unit at a price p therefore obtains surplus $v_i - p$, not accounting for any search costs described below. The value of a second unit of the good to a buyer is zero.

The game proceeds in two stages, beginning with search. One auction is high-visibility, indexed by $j = 0$, and the other auction is low-visibility, indexed by $j = 1$. In the first stage, buyers choose whether to engage in costly search or not. Each buyer draws an idiosyncratic search cost from a continuous distribution $G(c|v)$ with full support on $[0, \bar{g}]$, where $\bar{g} \geq \bar{v}$. The conditional aspect of the distribution allows us to accommodate correlation between valuations and search cost, though we assume that cost draws are independent conditional on v . Let s_i be the search decision of buyer i , where $s_i = 1$ signifies that buyer i searches and $s_i = 0$ that he does not. Searching buyers may participate in both auctions, while non-searching buyers are limited to participating in the high-visibility auction. Let N_1 denote the number of buyers who conduct a broad search and N_0 the remainder, so that $N_0 + N_1 = n$.

The search process we consider is similar to the fixed-sample search concept in the price dispersion literature (e.g., Burdett and Judd 1983, De los Santos, Hortacsu, and Wildenbeest 2012). In these models, buyers select upfront the number of price quotes to obtain, and then buyers receive this number of price quotes from a random set of sellers. In the current setting, the buyer's decision to conduct a narrow or broad search resembles a fixed-sample search in that it determines upfront the number of auctions a buyer will identify.

The second stage is the bidding subgame. Buyers receive an index $i \in \{1, \dots, n\}$ at random. The bidding proceeds in a sequential manner as in Peters and Severinov (2006). Buyers are given an opportunity, in order of their index, to bid in one of the auctions or pass. The auctioneer keeps track of the high bid, which is hidden, and the second-highest bid, which is

called the *standing price*. The first bid in an auction must be at least the starting price, and subsequent bids must be strictly greater than the standing price. After each bid, the standing price and identity of the high bidder are updated and made public. The buyer then has the opportunity to bid again in any of the auctions. After buyer i passes, each previous buyer is given the opportunity, in order of index, to submit a new bid or pass. Once all of these buyers have passed, buyer $i + 1$ is given the opportunity to bid. Bidding continues until all buyers pass, at which point the high bidder in each auction obtains the item at the final standing price, which constitutes the ending price.

B) Bidding subgame

In this section we demonstrate the existence of and characterize an equilibrium of the second-stage game that does not depend on a specification of beliefs. We take as given the search choices of the buyers, which are determined in the first stage. Let $A_i \equiv A(s_i)$ be a set including both auctions if $s_i = 1$ and only the high-visibility auction if $s_i = 0$.

We propose a bidding strategy that is based on Peters and Severinov (2006) but has a few important features: (1) it rules out “silly equilibria” such as those in which a buyer makes an arbitrarily high bid and others refrain from bidding at all; (2) it does not depend in any way on buyers’ beliefs about competitors’ types or the state of any auction of which the buyer is not aware; (3) it reflects the intuition that, among auctions with similar ending times, buyers prefer the auction with the lower current standing bid; (4) the bidding strategy extends that of Peters and Severinov (2006) insofar as we allow for heterogeneous buyers who are aware of different sets of auctions.

Definition 1 (Bidding Strategies). *The symmetric bidding strategy, $\beta^* \equiv \beta^*(v_i, s_i)$, is defined as follows: When it is buyer i 's turn to bid, then,*

1. *If buyer i is the current high bidder in any auction, he passes.*
2. *If the lowest standing price among auctions in A_i is $p \geq v_i$, then he passes.*
3. *Otherwise, buyer i chooses a single auction to participate in according to the following (complete, strict) lexicographic preference ordering:*
 - a. *first, auctions with lower standing prices are preferred;*
 - b. *second, auctions for which a bid has been placed since their last change of high bidder are preferred;*
 - c. *third, the low-visibility auction is preferred to the high-visibility auction.¹⁴*
4. *All bids are made in single increments of d above the current standing price of an auction.*

The first part of the bidding strategy rules out having high bids in multiple auctions, which reflects our assumption that the second unit of the good yields zero utility. The second part is consistent with logic of second-price auctions – buyers never bid above their own valuations. When buyers do choose to bid, the third part of the bidding strategy determines which auction they participate in. Finally, the fourth part of the bidding strategy sets the pace for the incremental convergence of the game to its outcome. Following bidding strategy β^* , standing prices increase incrementally by d until all non-winning bidders choose to pass. Buyer i passes

¹⁴ To see that the ordering is both complete and strict, note that it inherits both properties from part c. This is important because it means that there is no randomization between auctions, which would have made characterizing outcomes and therefore the profitability of deviations much more onerous. Eliminating randomization from the bidding strategy is also one reason we restrict the number of auctions to two. Randomization complicates the least economically interesting aspect of the proof of equilibrium – checking that there is no incentive to deviate at points in the history characterized by buyers having bid above their valuation. The familiar reader will recall the proofs in the online appendix of Peters and Severinov (2006).

when he is not a current high bidder and the lowest standing price in A_i is no longer below his valuation.

To characterize the equilibrium of the bidding subgame we borrow from Cremer and McLean (1985) the language of *ex post equilibrium*. An ex post equilibrium of an extensive-form game is defined as a strategy profile that is sequentially rational for an arbitrary set of beliefs about the state of nature. We employ this notion because it generates robustness in the sense that equilibrium predictions do not depend on assumptions on buyers' priors or rational expectations; and, as a corollary to this point, it uncouples outcomes in the bidding subgame from beliefs induced by type-dependent strategies in the first-stage search game.

Proposition 1. *There exists an ex post equilibrium of the bidding subgame in which buyers play according to β^* .*

All proofs are in a technical appendix available from the corresponding author upon request. While the proof of Proposition 1 borrows from that in Peters and Severinov (2006), it differs in a few important respects. First, because we are interested in ex post equilibrium, we avoid entirely the problem of specifying beliefs, especially off-path beliefs that are difficult to motivate. Second, the distinction between low- and high-visibility auctions necessitates some additional tools; we explicitly characterize the set of outcomes in which searching types set the price in the high-visibility auction and when they do not. We do this by constructing a price v_Γ^a , which is the predicted final standing price for the high-visibility auction in a world where only non-searching buyers participate. If the number of searching buyers at that price is greater than the supply of low-visibility auctions, then searching buyers will either win or set the price in the

high-visibility auction. When this happens there is price equality; otherwise, the final price of the two auctions may differ. Finally, because of the possibility that there are many high-valuation buyers who do not search, the equilibrium does not always allocate the items to the buyers with the highest valuations, and hence the equilibrium outcome may often be inefficient; this is not surprising in a model with search frictions.

C) Search and existence

The main contribution of our model is to incorporate buyers' first-stage search choices into a model of competing auctions. One component of the search model is to allow for low-visibility and high-visibility auctions. As an example, one could think of an auction with few keywords in the title as low visibility, and one with many as high visibility. The second component of the search model is the idiosyncratic costs that buyers face if they wish to identify the low-visibility auction. These costs reflect heterogeneity in cognition and time costs across buyers. Intuitively, these costs may be correlated with buyer types. For example, buyers with a high valuation might also have a high opportunity cost of time, suggesting that they more often enter the higher-priced, high-visibility auction.

For the equilibrium concept of the full game, we employ perfect Bayesian equilibrium. In general, it is not possible to separate multi-stage games of imperfect information and solve them by backwards induction. This is because beliefs in the later stages are derived from Bayes' rule conditional on strategies in the prior stages (see Fudenberg and Tirole 1991). Ours is a special case because we identify an ex post equilibrium of the bidding subgame, which breaks this dependence. Note that ex post equilibrium is strictly stronger than perfect Bayesian equilibrium, and therefore β^* is consistent with the latter.

Proposition 2. *There exist perfect Bayesian equilibria of the full game when buyers play β^* in the second-stage bidding game, such that:*

1. *In the first-stage game, buyers play threshold strategies; i.e., there exists a cost threshold c_x for every type $x \in V$ such that buyers with valuations $v_i = x$ who have $c_i \leq c_x$ search, while buyers with $c_i > c_x$ do not.*
2. *For $v_1, v_2 \in V$ and $v_1 \leq v_2$, we have $c_{v1} \leq c_{v2}$.*

The proof of existence involves the construction of a best-reply function, which incorporates the vector of thresholds c adopted by the other players into a vector of thresholds that is shown to be a best response. We show that this is a continuous mapping from a subset of real-valued vectors into itself, and employ Brouwer's fixed-point theorem to close the proof. It is easy to show that the profit from search is monotonically increasing in valuations, which implies monotonicity of expected surplus and therefore the threshold vector. While we do not demonstrate uniqueness, we do show (below) that any equilibrium of this game is guaranteed to exhibit price dispersion, which is the primary outcome of interest.

D) Price dispersion

The main result of our model is that for any equilibrium of the game in which buyers play β^* , there is price dispersion. In what follows, we define *price dispersion* formally as a characteristic of an equilibrium in which the expected prices of the low- and high-visibility auction are unequal. Note that there is not one universal metric of price dispersion in the literature, and instead there is a variety measures, including the price range, the variance, the coefficient of variation, the lowest two prices, and so on (Baye, Morgan, and Scholten 2006, Section 3.1). All are designed to capture the degree to which prices are unequal.

Proposition 3. *Any perfect Bayesian equilibrium of the full game is characterized by price dispersion.*

There are two mechanisms that cause price dispersion in the model. In the first, there is a chance that one or no buyers search, in which case the low-visibility auction sells (or fails to sell) at its minimum bid of zero. Although this seems stark, it comports with the idea of the “hidden gem” on auction sites such as eBay, in which an item sells for significantly less than its value because few buyers find it. The second mechanism generates a more continuous form of price dispersion. It occurs when the highest-valuation buyers choose not to search, and therefore drive up the price of the high-visibility auction. It is straightforward to show that this second mechanism is more important when $G(c|\nu)$ is stochastically increasing in ν (i.e., when higher-valuation buyers tend to have higher search costs).

3. EBAY DATA AND SEARCH TECHNOLOGY

A) The data

We collected data from eBay using a Java query tool, which we used to search listing titles and bodies for certain movie titles.¹⁵ We examine listings for 17 movie DVDs that were *Billboard* best sellers in August and September 2008.¹⁶ For each movie, we collected data on all auctions and posted-price “Buy-It-Now” options (BINs) (eBay provides both selling options)

¹⁵ The primary format on eBay is a modified second-price auction. eBay allows buyers to submit a maximum bid, where proxy bids are placed for the buyer when she is outbid, for an amount equal to the new bid plus an increment, up to her maximum bid. This format represents a hybrid of sealed-bid second-price auction, in the sense that buyers can submit one maximum bid and have eBay proxy bid for them, and an ascending-price auction, in that a buyer can increase her maximum bid during the auction. Bajari and Hortacsu (2004) describe proxy bidding (p. 461).

¹⁶ We started with 25 titles and eliminated TV series, several movies with titles that are easily confused, and three movies that did not have any matched pairs (we describe the matched-pair design below).

that were active between September and November 2008 for standard-format and Blu-ray DVDs. Our own search for listings was designed to capture all listings we expected at least some buyers to find in their searches, and our procedures are described in the Appendix.

The data include all listings regardless of whether a sale occurred. For each listing, the data record item characteristics such as condition (e.g., new), and auction characteristics such as listing-title wording and seller feedback score.¹⁷ After each transaction, the buyer can evaluate the seller with a positive (+1), negative (-1), or neutral feedback (0). The seller's feedback score is the sum of these feedbacks. As with many previous eBay studies, because nearly all feedback is positive, we use feedback score as our measure of experience. Nearly all sellers are identified uniquely in our data set by a seller identifier, which we use to construct sellers' listing histories.¹⁸

Our analysis examines the effects of wording differences on the differences in outcomes (e.g., prices) between very similar auctions (i.e., movie, format, edition, shipping method, seller feedback score, starting price, and ending time). Because wording and outcome differences occur between individual auctions, our unit of analysis is the auction pair. Note that group-level measures would fail to use some of the available variation, and using the auction as the unit of observation and including fixed effects for group in the regression analysis is not possible due to the rolling 24-hour time window that we use to define groups.

We limit the sample to auctions for new DVDs in order to avoid ambiguity over condition that is inherent to used DVDs.¹⁹ Uniform quality is important for ensuring that price

¹⁷ During the sample period, eBay expanded the condition variable from "New" and "Used" to five categories from "Brand New" to "Acceptable." We reclassify the categories to "New" and "Used."

¹⁸ Note that eBay anonymizes buyer identities and so the data do not allow us to track buyers across auctions.

¹⁹ We also exclude the small number of auctions that: have multiple units; are privately listed, which prevents us from identifying sellers; have a shipping fee over \$10, which are outliers; have an unlisted shipping fee; were delisted by the seller before the auction ended; or had a BIN option that was exercised (sellers can include a BIN option into an auction, which disappears when the first bid is placed). Also, we do not distinguish DVDs based on widescreen versus full screen because this aspect of our data set is incomplete. We drop the 3.7 percent of auctions with seller with less than 98 percent positive feedback because there were too few of these cases to construct pairs.

variations are not due to item/quality differences. Note that the item's condition is an automatic field that the seller must enter from a drop-down menu during the listing process (which is then included in the listing body and in our data set). Therefore, we do not depend on listing wording to identify a DVD as new.

We group all auctions by movie, format (DVD or Blu-ray), edition (e.g., collector's edition), shipping method (priority or standard), and seller feedback score ranges. Livingston (2005) finds that the marginal benefit of a higher feedback score for eBay sellers falls sharply as the score increases. Hence, we categorize sellers into the discrete feedback ranges of 1-5, 6-35, 36-215, 216-1291, 1292-7766, 7767+ (log base six) to capture this concavity. Next we construct all pairwise combinations of auctions that are in the same group and end within 24 hours of each other (i.e., a rolling 24-hour window).²⁰ When there are at least three auctions in the same group/period, each auction appears in multiple pairs. For example, for a group/period with three auctions, $\{A, B, C\}$, we construct the pairs, $\{(A, B), (A, C), (B, C)\}$. To account for the nonstandard error structure due to some auctions appearing in multiple pairs, we compute standard errors via nonparametric bootstrap.

Our primary data set contains 2,646 auction pairs, including 1,210 auction pairs where both auctions resulted in sale. We add shipping costs to starting and ending prices so that prices reflect the effective total prices that buyers face. Table 1 shows the movies in the data, ending prices, ending-price differences within pairs, and listing-title wording differences within pairs.

²⁰ Results are qualitatively similar for narrower time windows but are less precise due to the smaller group sizes.

B) Discussion of buyer search and listing-title wording

A primary way for buyers to identify the full set of concurrent auctions is to enter search terms into eBay's search bar.²¹ However, eBay's search results are sensitive to which search terms are used. This sensitivity is due to the operation of eBay's default search, which generally requires every word in a buyer's search string to appear in a listing's title for that listing to appear in the buyer's search results. For example, on September 27, 2010, a search for *Batman Begins* DVDs using the string "Batman Begins DVD" returned 699 listings, "Batman Begins 2005 DVD" returned 265 listings, and "Batman Begins on DVD" returned 5 listings. This difference is due to many titles omitting the year and most titles omitting "on."

The sensitive nature of the search algorithm suggests that a listing's visibility depends on the listing-title wording. Given the large number of possible search terms and the large number of concurrent auctions for popular items, buyers may face significant search costs to identify a full set of available auctions.²² Note that listing-title wording differences may also favor listings with titles that directly indicate the desired item even if listings with and without the words both appear in the search results. This would not change the basic intuition that listing-wording differences generate search costs for buyers to identify available auctions for the desired item.

²¹ Another search approach is to use a set of navigation check boxes on the left side of the eBay screen. This approach also entails search costs. For example, a user looking for the 2006 movie *Casino Royale* could type "Casino Royale" into the search bar; then choose the "DVD, HD DVD, & Blu-ray" check box to narrow the search to movies; then choose the "DVD" check box to exclude HD DVD and Blu-ray; then choose the "New" check box to exclude used items. Then the user must figure out among these results which are the full-screen version, widescreen version, collector's edition, and the 1967 movie that is also titled "Casino Royale." The user must also identify the seller's reputation score, the shipping fee, and so on.

²² Of course, price dispersion may arise from other frictions as well. For example, buyers may incur costs to monitor the standing prices of multiple auctions, and nonstandard buyer behavior may play a role (e.g., Baye and Morgan 2004). Empirical work suggests a role for nonstandard behavior in auction markets as well, although Podwol and Schneider (2013) and Schneider (2013) find that buyer behavior in auctions may be less nonstandard than some recent research suggests. Note that heterogeneous seller costs, which can generate price dispersion in the frictionless posted-price settings (e.g., Reinganum 1979), may not have the same effect in a frictionless auction setting. For example, Peters and Severinov (2006) obtain uniform prices with heterogeneous seller costs.

Table 2 shows that sellers with more experience include more words, and more key words such as “new,” in the listing title. Thus, it appears that writing effective listing titles is a skill acquired with experience and/or there is selection of more effective writers remaining in the market. Similarly, 54 percent of sellers with multiple new-DVD listings in our data set virtually always include the word “new” in their new-DVD listings, while 28 percent never do. Among the 18 percent of sellers with variation in “new,” the movie title length helps explain this variation: *listing* titles for movies with longer *movie* titles are less likely to include the word “new.”²³ A likely explanation is eBay’s listing title length limit of 55 characters, which may sometimes bind and cause sellers to not include words such as “new.”²⁴ Indeed, among the 18 percent of sellers with variation in “new,” listing for movies with movie titles over 30 characters are 39 percent less likely to include the word “new” compared to listings for movies with shorter movie titles. These results are in Table 3.

4. EVIDENCE ON SEARCH COSTS AND PRICE DISPERSION

In the theoretical model, unaware buyers are not aware of all auctions, and hence price dispersion arises as unaware buyers bid up the prices of some auctions over others. In the eBay setting, we have proposed that the particular subset of auctions that a buyer identifies depends in part on the wording of the auction titles and the buyer’s choice of search terms. This implies that eBay sellers can increase the visibility of their listings by including certain key words in their auction titles. For example, if auction 1 but not auction 2 includes the word “new,” then buyers who include “new” in their search string would discover auction 1 but not auction 2. Hence, including “new” is a technology that increases the visibility of auction 1 relative to auction 2.

²³ For example, *Harold & Kumar Escape from Guantanamo Bay* is less likely to include “new” than *Camp Rock*.

²⁴ eBay increased the character limit from 55 to 80 in July 2011, which is after our sample period.

In what follows, we estimate the relationships between listing title wording and three outcome that capture factors related to of price dispersion: (1) the probability that an auction results in sale; (2) the number of buyers that participate in that auction; and (3) the auction ending price. Our methodology captures the essential elements of a common approach in the empirical price-dispersion literature (e.g., Brown and Goolsbee 2002, Baron, Taylor, and Umbeck 2004, Lewis 2008). In these studies, price dispersion reflects differences between actual prices and the prices predicted from item and seller characteristics and time fixed effects.

Similarly, we calculate price dispersion as the pairwise price differences between auctions with the same item and seller characteristics, and approximately the same ending time.

A) Effect of listing wording on probability of sale, number of bidders, and ending price

Sixty-three percent of auctions in the estimation sample resulted in sale. We first examine whether auctions with more words in the listing title are more likely to result in sale. We use two different measures of wording differences between auctions. The first is the difference in total word count between listing titles in the pair. The second is the difference in whether the title includes the word “new.” In our inspection of listing titles, “new” is by far the most common wording difference, and a difference occurs in 41 percent of new-DVD auction pairs.²⁵ In contrast, other movie-DVD-related words like “special edition” and “disc” cause wording differences but only in a few percent of auction pairs, which does not provide sufficient power for precise estimates.

Let $R_j = 1$ if auction $j = 1, 2$ resulted in sale, and $R_j = 0$ if not. $\Delta R = R_1 - R_2$ is the difference within the auction pair. Z_j is an indicator for the visibility of auction $j = 1, 2$ within

²⁵ There is also little ambiguity in the data about whether the underlying item is actually new regardless of whether the seller included “new” into the listing title. Figure A1 in the Appendix is a screenshot of the eBay webpage where sellers enter item condition during the listing generation process. Sellers must complete the “Condition” field, and items appear in our data set as new if and only if the seller has selected “Brand New” from this drop-down menu.

the auction pair. In the case of eBay, $Z_j = 1$ if the listing title of auction j includes a particular word, and $Z_j = 0$ if not. Then $\Delta Z = Z_1 - Z_2$ is the within-pair difference in wording. For total word count, ΔZ represents the difference in the sum of words. Let $\Delta S = S_1 - S_2$ be the difference in starting prices within the pair. We control for ΔS in our analysis because starting price may affect the probability of sale, and starting price could be correlated with listing-title wording.

We estimate the following linear probability model,

$$[1] \quad \Delta R = \gamma_0 + \gamma_1 \Delta Z + \gamma_2 \Delta S + \epsilon,$$

where the unit of observation is the auction pair as defined above, and ϵ is a random error. A finding of $\gamma_1 > 0$ is evidence that additional words increase the probability of sale.

Table 4 reports the estimated models. The OLS estimates in columns (1) and (3) indicate that a one-word increase in word count, and the inclusion of the word “new,” increase the probability that the auction results in sale by 1.3 percent ($p<.01$) and 3.5 percent ($p=.03$), respectively. Thus, we find that auctions with additional words are associated with a higher probability of sale.

We next estimate the relationship between listing-title wording and the number of bidders who have placed bids in the auction. The prediction is that more words makes the listing more visible and hence attracts more bidders. The estimating equation is the same as Equation [1] except that the dependent variable is the difference in the number of bidders between auctions in the pair. These results are in Table 5. The OLS estimates in columns (1) and (3) indicate that a

one-word increase in word count and the inclusion of the word “new” correspond to 0.10 ($p=.09$) and 1.05 ($p<.01$) more bidders, respectively.²⁶

Finally, we estimate the relationship between within-pair wording differences and within-pair price differences. We again use Equation [1] as the estimating equation, but now the dependent variable is the difference in the ending prices between auctions in the pair. A finding of $\gamma_1 > 0$ is evidence that wording differences are associated with price dispersion. Table 6 reports the estimated models. The OLS estimate in column (1) indicates that a one-word increase in word count corresponds to a 16¢ increase in price ($p<.01$). The OLS estimate in column (3) indicates that auctions with the word “new” have an 80¢ higher price ($p<.01$) than auctions without “new.” Thus, we find that additional words correspond to a significantly higher price.

B) Identification and robustness

Our analysis makes use of both within-seller and between-seller variation in listing wording. The risk of relying on within-seller variation in wording is that this variation is not the result of a natural experiment and instead may reflect variation in underlying quality that is observed to the buyer and/or seller but not the researcher. This concern is relatively straightforward to address with the following instrumental-variables analysis.

Our first instrument uses the seller’s wording tendencies in her *other* listings to predict the wording in the listing of interest.²⁷ We generate an instrument for the word count of a listing title (or whether the listing title includes the word “new”) as follows. First, for each listing, we estimate by OLS a model in which the dependent variable is word count (or inclusion of “new”)

²⁶ We also estimated the probability-of-sale model using an ordered probit model (the dependent variable can take the values of -1, 0, 1), and number-of-bidder model using a Poisson model (we add twenty to the dependent variable to ensure positive values). Results are unchanged.

²⁷ Other listings includes that sellers other auction listings and also her BIN listings. Results are very similar when only the seller’s other auction listings are included.

and the explanatory variables are the full set of available item and auction characteristics.²⁸ The sample is the seller’s other auction and BIN listings for new DVDs in the data set. Second, we obtain the predicted word count (or “new”) for that listing using the estimated model for that listing. Finally, we use the difference in the predicted word count (or “new”) within each auction pair as the instrument for the actual difference in word count (or difference in “new”).

We calculate a second instrument for the difference in “new.” As discussed in Section 3, movie-title length helps to explain whether key words appear in the listing title. Because eBay had a *listing*-title limit of 55 characters during our sample period, the length of the *movie* title can limit the number of key words that fit in the *listing* title. For example, the movie title *Harold & Kumar Escape From Guantanamo Bay* has 41 characters, which leaves little room for additional words. This forces sellers to choose between words, and sometimes “new” may be excluded. To obtain our second instrument for the difference in “new,” we use the same procedure as above, except that in the first step we replace the movie-title dummy with a dummy for whether the movie title is over 30 characters long.²⁹

We estimate the IV regressions using two-stage least squares (2SLS) for the probability-of-sale analysis, the number-of-bidders analysis, and the price analysis. These results are in columns (2), (4), and (5) of Tables 4, 5, and 6. The estimates are broadly similar to the OLS results reported earlier.

As discussed in Section 3, most sellers systematically include or exclude certain words (e.g., “new” for new items) and systematically use either longer or shorter listing titles. This between-seller variation in listing wording is also not the result of a natural experiment, and an

²⁸ The characteristics are movie, edition, format, and shipping method. Note that this method requires each seller in a pair to have at least one other listing in the data set, which moderately reduces the sample size.

²⁹ We use this discrete measure rather than a continuous measure because character limits are likely only binding for longer movie titles. This indicator is a parsimonious way to capture the effect, but results are robust to alternatives.

obvious check of exogeneity for this variation is not available. However, after controlling for the observed item/auction characteristics (movie, edition, format, condition, shipping method, and seller experience), we believe the remaining wording tendencies across sellers are idiosyncratic and unrelated to item quality. We showed that seller experience is one factor that is associated with these differences, and we carefully control for experience by (1) defining our matched pairs on seller-experience ranges, and (2) including the difference in seller experience within the matched pair to control for any remaining experience difference within these ranges. We also chose to study new movie-DVDs because they are largely homogenous products with only a handful of distinguishing characteristics, all of which we control for. Finally, when we tested for endogeneity associated with within-seller variation in wording (above), we found that the results were not affected qualitatively.

5. CONCLUDING REMARKS

We have proposed a model in which auctions differ in the search costs required to find them. These search costs cause some buyers to conduct incomplete searches and consequently to be unaware of some of the available auctions. As a result, some buyers bid up the prices of some auctions above those of other auctions. Our empirical results provide evidence for the importance of search costs in explaining price dispersion in the competing-auctions setting of eBay.

As in posted-price markets, the presence of price dispersion in auction markets has efficiency implications. In posted-price markets, some sellers may charge a high price to exploit the unaware buyers. Hence, unaware buyers impose a burden on the remaining buyers who must now conduct costly searches to avoid the high-price sellers (Salop and Stiglitz 1977 first make this point). The logic in auction markets is somewhat different. Because unaware buyers bid only

in a subset of the available auctions, some auctions will have fewer competing buyers and hence a lower expected price. Thus, aware buyers may actually benefit from frictions because the reduction in prices in the less competitive auctions may exceed the search costs of finding these auctions. The lower prices in the less competitive auctions represent a simple transfer of surplus from sellers and unaware buyers to aware buyers. However, this price dispersion may also generate an inefficient allocation of items such as when unaware buyers are outbid in the more visible (i.e., competitive) auctions when they would have won the less visible auctions had they found them.

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Table 1: Summary statistics

Movie	Number of matched pairs	Mean end price	Mean difference in end price	Mean difference in number of words
Batman Begins	87	19.66	2.24	1.15
Camp Rock	197	12.72	1.82	1.78
Casino Royale	12	18.93	2.74	2.25
College Road Trip	16	10.24	2.60	1.69
Harold & Kumar Escape from Guantanamo Bay	9	15.12	1.59	0.78
Knocked Up	75	5.26	1.02	0.05
Die Hard 4: Live Free or Die Hard	3	17.16	3.70	0.33
Miss Pettigrew Lives for a Day	13	11.65	2.27	1.69
Pirates of the Caribbean: At World's End	73	8.45	2.20	0.26
Street Kings	38	10.01	1.99	2.24
The Bank Job	17	11.38	3.19	1.00
The Notebook	9	12.27	1.35	1.67
The Scorpion King 2: Rise of a Warrior	57	7.60	1.78	0.42
Transformers	608	24.39	2.21	1.62
All Titles	1,214	18.04	2.06	1.38

Notes: The sample consists of completed auctions for new DVDs that are in the estimation sample. The unit of observation is an auction pair. Each pair consists of auctions with the same movie, format (DVD/Blu-ray), edition (e.g., special edition), seller feedback score (within one of six ranges), shipping format (standard/priority), and ending within the same 24 hours.

Table 2: Listing-title wording by seller experience

Seller feedback score	Number of unique sellers	Number of listings	Median word count	Percent with “new”
0-5	10	13	5	15
6-35	37	48	7	33
36-215	139	186	7	45
216-1295	207	459	8	64
1296-7775	122	664	9	58
7776+	42	262	9	80
All	557	1632	8	61

Notes: The sample is auction listings that did and did not result in sale that form the matched pairs in our estimation sample. The middle two columns are listings for new and used items. The right two columns are listings for new items only. “Median word count” is the median number of words per listing title. “Percent with “new”” is the percent of listings that include the word “new” in the listing title.

Table 3: Effect of movie-title length on probability of including “new” in listing title

	(1)	(2)
Number of characters in movie title	-0.015*** [0.002]	
Movie title has over 30 characters		-0.391*** [0.040]
N	583	583

Notes: The unit of observation is the listing. The sample is all auction and BIN listings for new items for the 61 sellers who have listings both with and without “new” in the listing title. Seller fixed effects are included. The model is estimated by OLS as a linear probability model.

Heteroskedasticity-robust standard errors clustered at the seller level are reported in brackets.

*** indicates significance at the 1 percent level.

Table 4: Effect of listing-title wording on the probability of sale

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) 2SLS
Difference in word count	0.013*** [0.004]	0.021*** [0.005]			
Difference in "new"			0.035** [0.016]	0.050** [0.020]	0.057*** [0.020]
Difference in starting price	-0.039*** [0.002]	-0.040*** [0.002]	-0.039*** [0.002]	-0.041*** [0.002]	-0.041*** [0.002]
Difference in seller feedback	-0.020 [0.014]	-0.021 [0.015]	-0.020 [0.014]	-0.019 [0.015]	-0.019 [0.015]
Constant	-0.001 [0.008]	0.002 [0.009]	-0.000 [0.008]	-0.000 [0.009]	-0.000 [0.009]
N	2,646	2,419	2,646	2,386	2,386

Notes: The unit of observation is the auction pair. The dependent variable is the difference between indicators for whether the auctions in the pair resulted in sale (taking the values 1,0, or -1). The sample is listings of new DVDs whether or not they resulted in sale. “Difference in word count” is the difference in the number of listing-title words. “Difference in “new”” is the difference in the indicator variable for whether the listing titles contain the word “new” (taking the values 1,0, or -1). “Difference in starting price” is the difference in the effective starting price, which is the posted starting price plus the shipping cost. “Difference in seller feedback” is this difference divided by 10,000. Standard errors are calculated by nonparametric bootstrap and reported in brackets. Columns (4) and (5) are estimated with different sets of instruments, as described in the text. ** and *** indicate significance at the 5 and 1 percent levels, respectively.

Table 5: Effect of listing-title wording on number of bidders

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) 2SLS
Difference in word count	0.102* [0.061]	0.215** [0.100]			
Difference in "new"			1.046*** [0.206]	1.427*** [0.291]	1.450*** [0.286]
Difference in starting price	-0.390*** [0.018]	-0.394*** [0.019]	-0.393*** [0.018]	-0.396*** [0.020]	-0.396*** [0.020]
Difference in seller feedback	0.877** [0.345]	0.989*** [0.361]	0.879** [0.347]	0.979*** [0.376]	0.979*** [0.378]
Constant	-0.023 [0.118]	-0.043 [0.126]	-0.017 [0.115]	-0.050 [0.127]	-0.050 [0.126]
N	1,214	1,052	1,214	1,027	1,027

Notes: The unit of observation is the auction pair. The dependent variable is the difference in the number of bidders who have bid in each of the auction in the pair. The sample includes listings for new DVDs that result in sale. “Difference in word count” is the difference in the number of listing-title words. “Difference in “new”” is the difference in the indicator variable for whether the listing titles contain the word “new” (taking the values 1,0, or -1). “Difference in starting price” is the difference in the effective starting price, which is the posted starting price plus the shipping cost. “Difference in seller feedback” is this difference divided by 10,000. Standard errors are calculated by nonparametric bootstrap and reported in brackets. Columns (4) and (5) are estimated with different sets of instruments, as described in the text. *, **, and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 6: Effect of listing-title wording on price dispersion

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) 2SLS
Difference in word count	0.166*** [0.038]	0.160*** [0.062]			
Difference in "new"			0.811*** [0.153]	0.684*** [0.201]	0.608*** [0.195]
Difference in starting price	0.024** [0.012]	0.010 [0.012]	0.021* [0.012]	0.006 [0.012]	0.006 [0.012]
Difference in seller feedback	0.352* [0.180]	0.436** [0.180]	0.367** [0.182]	0.461** [0.182]	0.462** [0.181]
Constant	-0.089 [0.079]	-0.116 [0.079]	-0.084 [0.078]	-0.096 [0.081]	-0.097 [0.080]
N	1,214	1,052	1,214	1,027	1,027

Notes: The unit of observation is the auction pair. The dependent variable is the difference in price between auctions in the pair. The sample includes listings for new DVDs that result in sale. “Difference in word count” is the difference in the number of words in the listing title. “Difference in “new”” is the difference in the indicator variable for whether the listing titles contain the word “new” (taking the values 1,0, or -1). “Difference in starting price” is the difference in the effective starting price, which is the posted starting price plus the shipping cost, between the auctions. “Difference in seller feedback” is this difference divided by 10,000. Standard errors are calculated by nonparametric bootstrap and reported in brackets. Columns (4) and (5) are estimated with different sets of instruments, as described in the text. *, **, and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

APPENDIX: DESCRIPTION OF DATA PROCEDURES

Our Java query tool that we use to identify relevant eBay listings was designed to be inclusive in the sense of capturing as many listings as could be reasonably expected to appear in users' search results. Towards that end, we searched the title and body description of the listing for our search terms, while eBay by default only searches the listing title. Additionally, our search string included the movie title only without additional terms to narrow the search. For example, we searched for new DVDs for the 2005 movie "Batman Begins" using the string "Batman Begins" instead of "Batman Begins movie DVD (2005) new" or another permutation of possible search terms.

The wording is important because of the way that eBay's default search algorithm operates. The default algorithm during the sample period (which has changed only modestly since that time) is "All words any order" such that all terms in the search string must be present and exactly as spelled in the listing title for the listing to appear in search results. This rule can generate large differences in search results based on subtle differences in search strings. For example, on September 27, 2010, a search for DVDs of "Batman Begins" using the search string "Batman Begins on DVD" returned 5 listings, while a search using "Batman Begins DVD" returned 699 listings. The reason is that most listing titles do not include the word "on."

There are exceptions to the "All words any order" rule. Generally, the algorithm returns the singular and plural versions of search terms. The search is not case sensitive. For example, a search for the 2008 movie "Street Kings" returns listings for the 2002 movie "The Street King" and the 2003 movie "King of the Streets." Also, for some common words such as "DVD," the search additionally returns listings that do not contain the word "DVD" but appear in a corresponding eBay listing category. For example, a search of "Batman Begins DVD" returns all

listings that contain the words “Batman Begins DVD” and also listings in eBay’s “DVDs & Movies” listing category that contain the words “Batman Begins” without the word “DVD.”

Figure A1: Screen shot of eBay listing page

Help buyers find your item with a great title [Get help](#)

* Title [?](#)
Sideways (DVD, 2006)

Subtitle ([Free \\$0.50](#)) [?](#) [Sale!](#) Limited time.

* Condition [?](#)
Make sure you choose the right condition - you're responsible for accurately describing the item to buyers. [View all condition definitions](#)
Brand New ▾

UPC
 
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