Abstract:
Based on research documenting competition neglect, it was hypothesized that high demand markets would tend to exhibit excessive entry. This hypothesis was tested analyzing eBay data. As predicted it was found that a disproportionate number of sellers end their auctions during peak bidding hours, leading such hours to be less profitable. Additional analyses allow the categorization of sellers based on their sophistication (akin to level-k reasoning models) and show that the excessive entry is driven by sellers who realize that ending time is a strategic variable, but not that other sellers have the same insight (i.e. “level-1s”). Three alternative explanations, including unobserved heterogeneity of sellers ending auctions at different times of day, are ruled out. Finally, content analysis of 26 advice-books for eBay sellers shows that even the (presumably) sophisticated eBay users writing these books neglect the impact of competition on the profitability of entering markets with greater demand.

KEYWORDS: market entry, excess entry, auctions, last-minute bidding, competition neglect, level-k models, behavioral economics, bounded rationality.

JEL: D01, D21, D44, L22

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I. Introduction

Probably the most basic lesson from game theory is that when agents make decisions, they should take into account how the decisions of other agents influence the relative profitability of possible courses of action. Firms, for example, should make entry and production decisions based on residual rather than aggregate demand, taking into account the impact of competitors on the demand they face.

Experimental evidence from both economics and psychology, however, suggests that when people make decisions in a strategic setting, they tend to under-attend to the impact of actions of others on the profitability of different courses of action they can take, focusing instead primarily on variables that are under their own control. This competition neglect leads subjects to choose actions which would maximize their profits in the absence of competition, but which do not necessarily do so in its presence.

Moore and Cain (2004), for example, inspired by the performance-dependent market entry experiments conducted by (Camerer & Lovallo, 1999), performed lab studies where subjects chose repeatedly whether or not to take part in competitions over trivia questions, where payoffs were determined based on relative performance. They found that too many participants chose to compete when the trivia questions were easy, leading average payoffs to be lower for such competitions.\textsuperscript{1} Tor and Bazerman (2003) propose that subjects’ widely documented suboptimal behavior across three seemingly unrelated games (Monty Hall, “acquiring a company” and multi-person ultimatum game) have as a common denominator subjects’ failure to

\textsuperscript{1}Moore and Cain propose that, in addition to competition neglect, people’s estimates of the performance of others is more regressive (to the mean) than that of their own performance, and hence they systematically over-predict the performance of others in hard tasks, and under-predict it for easy tasks, exacerbating excess entry into easy competitions and insufficient entry into difficult ones.
take into account how other’s actions (and the rules of the game) influence the profitability of different possible courses of action.

Some evidence of competition neglect has already been obtained outside the lab: Moore, Oesch and Zietsma (2004) interviewed 54 individuals who considered starting a new company (34 did and 20 did not) and asked them to describe the process behind their entry decision. Their answers were coded, among other things, by whether they referred to external (e.g. competition or economic climate) or internal factors for their entry discussion. Consistent with competition neglect, just 10% of all their arguments were coded as based on external factors.

Applying the notion of competition neglect to a real world market entry setting, a novel prediction arises. Consider the decision sellers face when choosing among multiple possible markets to enter (e.g. location for a new restaurant, music genre for a new radio station or time of year for releasing a new product). If in line with competition neglect they under-attend to the impact of other entrants on the profitability of different markets, they will tend to engage in excessive entry into high demand markets (e.g. there will be too many restaurants opening (and hence closing) downtown, too many hip hop radio stations and too many new gadgets released right before Christmas).

Testing this prediction with field data is challenging, of course, because markets that differ in aggregate demand are likely to also differ in other dimensions that are relevant for entry, such as operational costs, barriers to entry, or uncertainty. Disproportionate entry across markets with different demand levels, therefore, could not unequivocally be attributed to competition neglect. This paper tests this prediction in a setting which is free of such confounds: eBay sellers’ decision of what time of day to end their auctions.
Abundant research has documented that although online auctions typically last several days, a substantial fraction of bids are placed when only a few minutes remain on auctions’ clocks (see e.g. Bajari & Hortacsu, 2003; Brint, 2003; Ockenfels & Roth, 2006; Roth & Ockenfels, 2002; Wilcox, 2000). The sample of auctions for DVD movies used in this paper is no exception: almost 40% of winning bids in it arrived during the last sixty minutes of the auctions in which they were placed.  

Because bidders tend to bid as auctions are about to end, an auction’s ending time influences which (and possibly how many) bidders it receives. One can hence conceptualize the time at which an auction ends as a local market where demand corresponds to the number of bidders who are online at the time when the auction ends, and supply to the number of (possibly neglected) other auctions that are also ending.

If the number (and valuation) of bidders online was constant through time, then no market would be more appealing than the next. Bidding however, of course does not occur with the same frequency throughout the day. People are less likely to be online when they are, say, working or eating. In the sample of auctions for DVD movies used in this paper, for example, there are more than seven times the number of bids being placed during the hour in which most bidding occurs (6PM) than during the hour of least bidding (1AM).

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2 Several explanation have been proposed for late bidding, including: (i) tacit collusion on the part of bidders who use the probability that a late bid will not be registered by the website, as a randomizing device leading to lower expected prices, (ii) rational bidders’ best responding to naïve ones that bid incrementally higher amounts in the presence of competition (both originally proposed by (Roth & Ockenfels, 2002)), and (iii) bidders bidding late in order to avoid revealing their private valuation for common-value goods (Bajari & Hortacsu, 2003; Peters & Severinov, 1997; Roth & Ockenfels, 2002; Wang, 2003). For a review of this literature see section 3 in (Bajari & Hortacsu, 2004).

3 Throughout the paper I report time of day using Pacific Standard Time (PST), regardless of where the seller or the bidder is geographically located, because that’s the only time that is reported on eBay’s website.
The prediction arising from competition neglect is that too many sellers will choose to end their auction during times of day when most bidders are online and too few during those hours when less bidders are present.

Studying market entry with ending time data from online auctions for DVD movies has two important advantages. The first is that, as was already mentioned, the different markets that sellers can enter here differ only in aggregate demand; fixed and operational costs, expertise requirement, etc. are constant across markets. The second important advantage is that by studying a commodity (DVD movies), one can easily infer what a seller would have obtained had she entered a different market.

This is an important feature of the data. In the paper most closely related to the present research, (Einav, Forthcoming) finds that film distributors tend to release their blockbuster films during major holiday weekends, exacerbating the seasonality present in movie-theatre revenues (he does no discuss the potential role of competition neglect on his findings). Although Einav’s estimates suggest that distributors would be able to increase their revenues by releasing some of their blockbuster films during non-holiday weekends, any single film is only released once, of course, and hence predicted revenues rely directly on the assumptions that are employed to construct counterfactual demand levels. ⁴

The hypothesized role of competition neglect on market entry is explored in more detail through a simple two-market (i.e. period) auction model where bidders’ bidding times are exogenous (e.g. set by society’s conventions of when to work, eat and sleep) and sellers’ ending time decisions are endogenous.

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⁴ In Einav’s case, the assumption is that demand for a given film depreciates at the same rate independently of when it is released.
Importantly, sellers differ in their degree of sophistication, in particular, in the extent to which they take into account the ending time decisions of other sellers. Level-0 sellers do not even realize ending time is a strategic variable and hence randomize between the two markets. Level-1 sellers realize ending time is a strategic variable but neglect the fact that other sellers also have this insight and hence they all end their auctions during the period of peak demand.

Finally, level-2 sellers (the highest level in the model) realize the bias of level-1s and hence systematically end their auctions during the off-peak period. The model predicts that if there are more level-1s than level-2s, i.e. if there exists competition neglect on average, then: (1) the peak demand market will capture a disproportionate share of sellers, and hence (2) the peak demand market will have lower expected payoffs for sellers.

The data support both predictions. In particular, consistent with prediction 1, both supply (i.e. auctions ending) and demand (i.e. bids being placed) peak during the same hours of the day (between 5 and 8 PM), but the peak of demand, which captures 25% of all bids, is significantly less pronounced than the peak of supply, which clusters 35% of all auctions.

The data also support the notion that this excessive entry is driven by the subset of sellers who realize that ending time is an important variable, but who fail to take into account that others sellers realize this too (i.e. by level-1 sellers). In particular, sellers who pay a fee that allows them to determine the precise ending time of their auction cluster their ending times even more than average sellers (47% of their auctions end during peak demand hours). Similarly, sellers who end consistently at the same times of day are significantly more likely to end their auctions during peak demand hours. Prediction 2 also finds support in the data. Items ending during peak demand hours see their probability of sale diminished by 9.6%.
These results are interpreted as supporting the hypothesis that sellers of online auctions fall prey to competition neglect and set the ending time of their auctions ignoring the decisions of their competitors. Three alternative explanations are explored; they all fail to receive empirical support.

The first is that sellers ending auctions at peak demand hours are unobservably different than those ending at off-peak hours, the second is that the disproportionate supply peak is driven by cost differentials associated with listing items at different times of the day, and the third that auctions ending during the hours of peak demand have lower expected payoffs but higher variance, and they are hence chosen by risk seeking sellers.

In addition to using the sample of DVD auctions to rule out these specific alternative explanations, a sample of 26 books providing advice to eBay sellers was analyzed to study ending time strategies explicitly. The ending time recommendations of each book were coded as corresponding to level-0s (e.g. if they claim that because eBay is a 24 hour business ending time should not matter), level-1s (e.g. if they suggest ending auctions between 5 and 8 PM because that’s when most people are online) and level-2s (e.g. if they point out that although demand peaks in the early evening, so does supply, and hence sellers should end their auctions during the off-peak hours). Consistent with the notion that sellers, on average, engage in competition neglect, of the 26 books examined, eight were coded as giving level-0 recommendations, fourteen as giving level-1 ones, and just two as giving a level-2 recommendation.  

The content analysis of the book shows that sellers not only behave as if they ignored the decisions of other sellers when choosing the ending time of their auction, but that they actually and literally do so. Note that people writing books about eBay are presumably more

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5 The remaining two books recommended the seller to experiment with different times of day. Such recommendation does not unambiguously fit into any of the three types.
sophisticated than the average eBay user and hence the distribution of levels across books is arguably an upper bound of the distribution across sellers.

The reminder of the paper is organized as follows. Section II presents a simple two-market entry model, section III reports the empirical analyses that find evidence consistent with both predictions from the model, section IV explores the three alternative explanations alluded to above, section V summarizes the ending time recommendations of the 26 eBay books that were reviewed and section VI concludes.

II. Analytical framework

Setup

This model consists of an English auction market containing an exogenously fixed number of bidders ($B$) and sellers ($S$). There are two time periods, 1 and 0, which will be referred to as markets for the remainder of this section. $p_{b,i}$ and $p_{s,i}$ represent the proportion of buyers and sellers, respectively, entering market $i$, with $i = 0, 1$. $p_{b,i}$ is exogenously determined, with $p_{b,1} > p_{b,0}$, i.e. market 1 corresponds to the period of peak demand.  

All auctions are for one unit of the same commodity, valued at $v$ by buyers, and at $c$ by sellers, with $v > c$. Bidders are assumed to always bid $v$ and sellers to always start their auctions at $c$.

Sellers’ payoffs depend on how many bids they receive. They obtain $0$ if they receive zero bids (and hence do not sell), $c$ if they receive exactly one bid (because the starting price is $c$), and $v$ if they receive two. The expected number of bids a seller receives, in turn, depends on the total number of bidders and sellers participating in the market she enters.

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6 There is an important distinction between two decisions bidders make: what time of day to bid, and what auction to bid on once online. The model assumes that timing is exogenous, which is not inconsistent with earlier work showing that auctions are chosen endogenously (Bajari & Hortacsu, 2003; Reiley, 2005; Simonsohn & Ariely, 2005)
The probabilities associated with obtaining a payoff of \( v \), \( c \) and 0, can hence be expressed as a function of the number of bidders entering market \( i \) (\( B_{pb,i} \)) and the number of sellers entering market \( i \) (\( S_{ps,i} \)). Table 1 maps \( B_{pb,i} \) and \( S_{ps,i} \) into the expected profits associated with entering market \( i \) (\( \mathbb{E}[\pi_i] \)). The table also shows that \( \mathbb{E}[\pi_i] \) is non-increasing with respect to \( p_{s,i} \).

Since the payoff function suffers from discrete changes at two key thresholds (when there is exactly one bid per seller, and when there are exactly two bids per seller), the table reports the mapping within the resulting three intervals, labeled as cases (i), (ii) and (iii).

For example, in case (iii), there are more sellers than buyers, so some sellers (\( B_{pb,i} \) of them) will receive one bid and hence a payoff of \( c \), while the rest (\( S_{ps,i} - B_{pb,i} \)) will obtain 0 bids and hence a payoff of 0. The expected payoff for entering this market, therefore, is \( c \frac{B_{pb,i}}{S_{ps,i}} \).

***Table 1***

Equilibria

Equilibrium requires expected payoffs across both markets to be the same, i.e. that \( \mathbb{E}[\pi_1(S_{ps,1}, B_{pb,1})] = \mathbb{E}[\pi_0(S_{ps,0}, B_{pb,0})] \). Based on Table 1 it is easy to see that this requires both markets to have a relative number of sellers and buyers such that they are under the same case, because expected payoffs do not overlap across cases.

The equilibrium condition is met in case (ii) if
\[
\nu \left( \frac{B_{pb,1} - S_{ps,1}}{S_{ps,1}} \right) + c \left( 1 - \frac{B_{pb,1} - S_{ps,1}}{S_{ps,1}} \right) =
\nu \left( \frac{B_{pb,0} - S_{ps,0}}{S_{ps,0}} \right) + c \left( 1 - \frac{B_{pb,0} - S_{ps,0}}{S_{ps,0}} \right).
\]

Considering that \( p_{b,0} = (1-p_{b,1}) \) and \( p_{s,0} = (1-p_{s,1}) \), this
condition is met iff $p_{s,i} = p_{b,j}$. Similarly, the equilibrium condition is met in case (iii) when

$$c \frac{Bp_{b,0}}{Sp_{s,0}} = c \frac{Bp_{b,1}}{Sp_{s,1}}$$

which is also true iff $p_{s,i} = p_{b,i}$.

These results are intuitive: equilibrium is attained if sellers enter markets in the same proportions as buyers do.

**Predicted disequilibrium**

For equilibrium to be attained, sellers must behave as if they held accurate beliefs about the actions of other sellers. In the presence of competition neglect, however, sellers systematically underweight the impact of the actions of other sellers on their own payoffs. A common approach to modeling imperfect beliefs about the strategic behavior of others has been to categorize players according to a hierarchy of types indexed by levels, where a type’s level indicates how cognitively sophisticated she is (see e.g. Binmore, 1988; Camerer, Ho, & Chong, 2004; Nagel, 1995; Stahl, 1993; Stahl & Wilson, 1994). Typically in such models level-0s choose randomly, level-1s best respond to the random behavior of level-0s, level-2s best-respond to the behavior of (a sometimes degenerate) distribution of level-0s and level-1s, and so on.

Although the existing literature typically equates the sophistication of players with the number of iterated steps of reasoning in which they engage in, in this setting a slightly different classification is more useful. In particular, assume sellers are either level 0, 1 or 2, where:

- Level-0s do not consider the market-entry decision a strategic one, and hence randomly decide what market to enter, doing so in the same proportion as buyers.

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7 If both markets are in case (i), any $p_{s,i}$ constitutes an equilibrium.

8 Typically, iterated-reasoning models assume that leve-0s choose with equal probability all possible courses of action. In this particular setting it seems more realistic to assume that if a seller is choosing carelessly when to end
• Level-1s realize market-entry is a strategic decision, but (in line with competition neglect) ignore the choices of level-0s (and other level-1s), and hence they (all) enter market 1.

• Level-2s also realize market-entry is a strategic decision, and they do take into account the decisions of level-0s and level-1s. They hence enter market 0 until \( p_{s,0} = p_{b,0} \) and then (if there are any level-2s left) enter market \( i \) with probability \( p_{b,i} \).

Market outcomes depend on the relative proportion of level-2s and level-1s. If there are more level-2s than level-1s, an equilibrium is attained since \( p_{s,i} \) will equal \( p_{b,i} \). If, in line with the experimental literature, there are more level-1s than level-2s there will be excess entry into market 1 (\( p_{s,1} > p_{b,1} \)). Note that because level-0s enter the market in the same proportion as buyers do, they are not the ones responsible for excessive entry. Indeed, if everyone was a level-0 the markets would be in equilibrium.

Because \( \partial E[\pi_i] / \partial p_{s,i} < 0 \), if there are more level-1s than level-2s the expected profit will be higher in market 0 than in market 1. This difference in expected payoff could be caused by a difference in expected price, in probability of sale or both. If all items are sold in both markets (i.e. both markets are in case ii), the difference in \( E[\pi_i] \) is caused by a lower expected final price only (0, C or V). If some items remain unsold in both markets (i.e. both markets are in case iii), the difference in expected payoffs is caused by lower probability of sale only.

If the gap in entry between both markets was big enough to place market 0 into cases (ii) or (i) and market 1 into case (iii), there would be both a price and a probability-of-sale
difference, with the low demand period experiencing 100% sale and an expected final price, conditional on sale, between $c$ and $v$, and the high demand period experiencing a lower probability of sale with an expected final price equal to $c$, conditional on sale.

In sum, if in line with the experimental evidence there are more level-1s than level-2s the following predictions arise:

**Prediction 1:** The period of peak demand will coincide with the period of peak supply, but supply’s peak will be more pronounced, leading to a lower bids-to-auctions ratio for the peak demand period.

Prediction 1, in other words, states that the peak of aggregate demand (most bidding) coincides with the trough of residual demand (bids over auctions).

Because a seller’s expected payoffs depend directly on the ratio of bids-to-auctions (i.e. residual demand),

**Prediction 2:** The period of peak demand will have lower expected payoffs for sellers, which depending on the resulting ratios of sellers to bidders can materialize via lower probability of sale, lower expected price, or both.

The next section will assess the empirical validity of both of these predictions using data from eBay auctions.

### III. Empirical Analyses

This section begins by describing key features of eBay auctions. It then describes the source of the data and explains the creation of the subsample used for testing prediction 2. After some descriptive statistics it presents evidence consistent with the two predictions and with the
notion that excessive entry into peak demand hours is driven by the subset of sellers who
intentionally choose the more popular ending times for their auctions (i.e. by level-1s).

A. Overview of the functioning of eBay

For readers unfamiliar with the functioning of eBay, this subsection briefly summarizes
the key features needed to understand the analyses presented in this paper. Further information
can be found in (Bajari & Hortacsu, 2004) and directly on eBay’s help page
(http://pages.ebay.com/help/).

Anybody can become a seller and/or a buyer on eBay. Although many sellers are
individuals who sell sporadically, eBay is progressively attracting sellers who use eBay to sell
large numbers of items. Indeed, many stores use eBay as their main distribution channel for both
new and used items.

eBay does not utilize unified product identifiers (e.g. ISBN or UPC). 9 Instead, sellers
write a description of the item they are selling (e.g. “Brand new Monsters Inc. DVD”) and
categorize their item in one of eBay’s categories (e.g. DVD movies). When listing an item,
sellers must also choose a variety of strategic variables such as the starting price (i.e. the
minimum bid which can be placed in the auction), shipping charges, and the duration of the
auction (3,5,7 or 10 days). In addition to the starting price, sellers can place a secret reserve
price which is the minimum bid required to win the auction: bids between the starting price and
the secret reserve can be placed, but cannot win the auction. The secret reserve is revealed only
once a bidder bids above it. Sellers can also post a fixed-price at which a bidder can directly buy
the item, immediately ending the auction (referred to as the “buy-it-now” price).

9 This has actually changed since the data was collected. eBay now does provide sellers with the opportunity to
include information about the UPC or ISBN of the product they are selling.
IMPORTANT: By default, auctions end at the same time of day as when they are listed. For example, suppose a seller sets up a three-day auction at 10:17AM on Monday: the auction will start immediately and hence end on Thursday at 10:17AM. Sellers have an option to pay a 10-cents scheduling fee that allows them to start (and hence end) their auction at a time other than when they list it. This linkage between listing and ending time creates a potential alternative explanation for a more pronounced peak for auctions than bids, explored in detail in section IV.

Every time an item is sold, both the buyer and the seller have the opportunity to rate each other with a positive (+1), negative (-1) or neutral score (0). Many have investigated the relationship between seller reputation and auction performance, for reviews see (Bajari & Hortacsu, 2004; Resnick, Zeckhauser, Swanson, & Lockwood, 2006). Here this variable will only be used as a control for experience.

The sum of all existing ratings is displayed next to buyers’ and sellers’ usernames and hence it makes agents’ reputation readily available to everyone. Since the vast majority of ratings are positive, a user’s rating is a good proxy for their experience.

B. The Data

Source of the data

eBay directly provided most of the data. In its raw form the data consists of 518,064 online auctions taking place in October of 2002 in the DVD-movie category, and their corresponding 1,203,648 bids. eBay did not, however, provide information on the time-of-day

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10 I thank Dan Ariely for granting me access to these data, which he obtained after a long period of negotiation with eBay.
when auctions ended or bids were placed. These key variables were obtained independently, utilizing a custom designed computer program.

DVD movies (a commodity) were chosen as the good to be used in the analyses in order to reduce unobserved heterogeneity to a minimum. eBay, as was mentioned earlier, does not utilize unique product identifiers for their listings, so both bidders and researchers must rely on item description written by sellers to identify the specific item being auctioned. A small subsample was hence created where movie-titles were individually identified. The full dataset was used to assess hourly patterns in bidding and ending times (to test prediction 1), and the subsample to study the impact of such patterns on sellers’ expected payoffs, allowing the usage of movie-title fixed effect (to test prediction 2).

Subsample

To construct a subsample where the movie title of the item being auctioned could be identified, it was necessary to first create a list of titles against which the sellers’ descriptions could be compared. In order to obtain a high number of observations per movie-title, this list consisted of popular DVD titles, in particular, of movies that were in one of two top-30 bestseller lists at http://www.boxofficemojo.com.

Since a high percentage of bestsellers from one month are also bestsellers in nearby months, two temporally distant lists were chosen: one from the month prior to the sample, September of 2002, and one from slightly over a year prior to the sample, July 2001. Six of the sixty titles were too similar to other movie-titles, introducing uncertainty as to the exact movie being auctioned, or had too few observations and hence were not used. The subsample also excludes auctions with a reserve price (1.1%) and those offering the “buy-it-now” option
(13.6%). After these exclusions the subsample contains 54 movie-titles offered in a total of 8,056 auctions, by 2,404 different sellers, and receiving a total of 36,926 bids.

**Descriptive Statistics**

Unless otherwise noted, all summary statistics refer to the subsample of 8,056 auctions. Means, medians and standard deviations for variables used in the analyses are presented in Table 2. Seventy-eight percent of auctions in the subsample resulted in a sale. The average price for sold items was $10.31 with a standard deviation of $3.01. Importantly, variation in final price occurs not only across movie titles, but also within. The average variation coefficient within a movie title is 23.4%, only 6 percentage points below the coefficient computed for the whole sample.

Surprisingly, eBay collects shipping fees information only for items paid through their internal payment system (now, but not in 2002, consisting of *paypal®*) and hence 28% of the data does not contain information on shipping charges. When shipping is added as a control, therefore, sample size will be reduced.

***Table 2***

It is worth noting that the auction market that is analyzed is not highly concentrated. The top-4 sellers offered just over 3.5% of all auction. There are 2,404 different sellers in the subsample, and 27,480 different sellers in the full sample of 518,064 auctions.

**Late Bidding**

Figure 1 shows the percentage of all, winning and first bids arriving towards the end of the auction; consistent with prior studies, it shows a marked tendency for late bidding. Twenty-
percent of all winning bids are placed with just 1 minute left in the auction, over half of them with less than 60 minutes left and ten percent of auctions receive their first bid with less than three hours to go.

*** Figure 1 ***

C. Prediction 1 - Timing of bids and auctions

According to prediction 1, sellers disproportionately choose to end their auctions at the time of day when most bids are placed. Figure 2a plots the hourly distribution of auctions’ ending time, and of bids placed, for the full dataset of 518,064 auctions. Figure 2b plots the ratio of the percentage of bids placed to the percentage of auctions ending in 1-hour intervals. For example, 3.9% of all auctions end between 8AM and 9AM while 4.7% of all bids are placed during that hour, leading to a ratio (from now on referred to as B/A), of 1.21.

***Figures 2a and 2b***

Figure 2a shows that the number of bids placed by hour increases consistently during the day, until it reaches its peak at 6PM. Auctions show a similar pattern, although they also reach a local peak at 11AM. Consistent with prediction 1, the auction’s peak is much more pronounced than the bids’ peak; between 5:00PM and 8:59 PM bidders place 25% of their bids, while sellers set 34.5% of their auctions to expire. This is highlighted by the fact that the B/A obtains its lowest point when the number of bids being placed peaks: 0.65 at 6PM (see Figure 2b). Note that if the different markets were in the equilibrium described in the model, B/A would be constant an equal to 1 throughout the day.

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11 Recall that all times are expressed in Pacific Standard Time, regardless of the location of the seller or bidder.
12 If the hourly distribution is plotted using only the subsample of 8,065 auctions the same general pattern arises, but B/A is noisier between 1AM-5AM given the small number of observations involved.
13 Perhaps because sellers think that bidding has a local peak during lunch-time.
To test the significance of the pattern consistent with prediction 1, i.e. with the peak of demand coinciding with the trough of B/A, a regression was estimated where each hour of each day in October of 2002 was an observation (i.e. $N=24*31=744$), the dependent variable was the B/A during that hour, and the independent variable was percentage of bids placed during that hour. Consistent with prediction 1, the coefficient for percentage of bids proved negative and statistically significant ($\beta_{B/A} = -0.12$, $SE = 0.0083$, $R^2 = 0.222$). One interpretation of this result is that at times when aggregate demand was highest, residual demand was lowest. Note that the purely mechanical effect of the percentage of bids being both in the numerator of the dependent variable and of the independent variable works against the hypothesis of a negative association.

D. Is the supply-peak intentional?

As was mentioned above, auctions end, by default, at the same time of day as when they are listed. Because ending time, unlike starting price or duration for example, is not a variable which sellers explicitly determine, it is likely that they differ in how much thought (if any) they put into setting it.

According to the model, excessive entry is driven by sellers who purposefully choose the ending time of their auctions (level-1s). Two independent tests of this proposition were conducted; they differ in how they proxy for intentionality. The first concentrates on a small subset of auctions for which sellers chose to pay a scheduling fee allowing them to modify the default ending time. The main advantage of this approach is that it is very likely that sellers explicitly choosing an ending time for their auction are more aware of the ending time decision than the average seller, and hence they are less likely to be level-0s. The main disadvantage of this approach, however, is that very few auctions were listed using this scheduling fee. Only 702
of the 27,480 sellers in the sample ever use the scheduling fee, and only 8,302 of the 518,064 auctions (around 1.6%) were listed using the scheduling fee.

The second approach proxies for intentionality with the consistency with which sellers choose ending time. It relies on the logic that sellers who systematically choose the same ending times for their auctions are more likely to be doing so intentionally than sellers who end their auctions at different times of the day. The main advantage of this approach is that it includes the vast majority of auctions in the sample (only sellers with very few auctions are excluded). Its main disadvantage is that consistency is a noisy proxy for intentionality; sellers may intentionally spread out their auctions through different times of day, or they may cluster their auctions around the same time because of external constrains.

First approach: scheduled auctions. Consistent with the proposition that sellers who intentionally set ending time are more likely to choose peak demand hours, scheduled auctions show a much more pronounced peak than the entire sample: 47.7% of them end between 5PM and 8PM, a significantly larger share than the 34.5% of all auctions ($\chi(1)=785, p < .0001$).

Second approach: consistency of ending times. Utilizing consistency of ending time as a proxy for intentionality poses a minor technical challenge. Suppose all sellers chose ending time randomly, drawing from the same probability distribution. Because of sampling error, ex-post, some sellers would have higher variation in the ending times of their auctions than others; furthermore, on average, sellers with an ex-post lower variation in ending time would be more likely to have drawn the most common ending times (i.e. the peak times).

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14 For example, suppose the distribution from which all sellers choose an ending time was 10AM with 30% probability, and 6PM with 70%. If we know that a seller, ex-post, ended her two auctions at the same time (i.e. low variance), there is an 84.5% that both auctions ended at 6PM, and only 15.5% of them being at 10AM; low variance samples over-represent likely outcomes.
Unfortunately, this purely mechanical relationship between ex-post variance within the sample and frequency of numbers in that sample works in the same direction as the causal explanation being tested. One way around this potential problem is to measure variation in ending times from one subset of a seller’s auctions, to predict the ending times in a different subset of auctions, of the same seller.

The full sample of 518,064 auctions was hence divided into two: auctions ending during the first and second halves of October. Within each half, the average deviation in minutes among auctions by the same sellers was computed and then matched to the seller’s auctions in the other half of the month.

Average time deviation does not take date into account. For example, a seller with just two auctions, one ending on a Monday at 6:45PM and one on a Wednesday at 6:55PM, would have an average deviation of 5 minutes. Sellers with less than 5 auctions in one half of the month were excluded from this analysis (the results are robust to excluding sellers with less than 3 or less than 10 auctions).

Considering that variation in ending time in one half of the month is used to predict behavior on the other half, it is useful to compute the correlation of standard deviations, within sellers, between the two halves. This correlation proved positive and significant ($r = .42, p < .0001$), indicating that sellers who tended to systematically set auctions around the same time of day in one half of the month, also did so on the other half. This suggests that it is meaningful to characterize seller types based on the standard deviation in the ending times they choose.

Figure 3 plots sellers’ average percentage of auctions ending during the peak demand period of 5PM to 8PM by sellers’ decile of standard deviation in ending times. It shows, consistent with the notion that sellers who intentionally choose the ending time of their auction
are more likely to choose peak demand hours, that sellers with lower standard deviations (in one half of the month) are more likely to set the ending time of their auctions during the period of peak demand (in the other half). For example, sellers who are in the lowest decile of standard deviation set around 39% of the auctions during the period of peak demand, while those in the highest decile do so for just 27% of them.

***Figure 3***

Note that, consistent with the model’s assumption that level-0 sellers enter markets in the same proportion as bidders, the proportion of auctions listed during the hours of peak demand by sellers identified as mindless (i.e. high standard deviation of ending time) is very similar to the proportion of bids placed during such hours (27% and 25% respectively).

In sum both approaches provide evidence consistent with the notion that the excess supply of auctions during periods of peak demand is driven by sellers who consciously decide the ending time of their auction.

E. The role of experience on the timing of bids and auctions.

Although the dataset does not contain information on buyer or seller experience per se, it does contain the bidders’ and sellers’ reputation (described in some detail in section II.A). As was mentioned above, earlier research has investigated the impact of reputation on bidders’ decisions; here I use reputation only as a proxy for experience. eBay’s feedback score is not perfectly correlated with experience because not all transactions are evaluated; sometimes experience increases and reputation does not. Similarly, when an agent receives a negative evaluation her reputation decreases while her experience clearly does not. Nevertheless, bidders’
and sellers’ reputation are likely to be very highly correlated with their experience and hence the former was used as a proxy for the latter.

There is ample variation in the reputations of bidders and sellers in the sample. In the case of bidders, it ranges from -5 to 24,895, with a mean of 116.9 and a standard deviation of 312.3. While for sellers it ranges from 0 to 88,632 with a mean of 479.8 and a standard deviation of 1499.8.

To assess a possible relationship between experience and the timing of auctions and bids, sellers and bidders were classified into quintiles, based upon their reputation rating. The percentage of bids being placed and of auctions ending during the peak demand hours of 5-8PM were then computed for each of the quintiles. The results are presented in Figure 4. The figure shows that, regardless of their experience, bidders place around 25% of their bids between 5-8PM. 15 The figure also shows that, although for all quintiles it is the case that the proportion of auctions ending between 5-8PM is greater than the proportion of bids being placed at those times, sellers with more experience cluster their auctions even more. 16 On interpretation of Figure 4 is that experience turns level-0 sellers into level-1s, but not into level-2s, at least on average.

It is somewhat surprising that sellers with more experience do not appear to “learn.” One explanation for this pattern is that sellers only receive feedback on the absolute profitability of ending their auctions at the times of day when they do end them, but not on the opportunity cost of ending them at a different time. If sellers do not experiment with different ending times, they simply do not receive the kind of feedback that would allow them to learn that they are selling in

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15 Consistent with the assumption in the model that bidders’ bidding time is exogenous (at least with respect to experience).
16 Highly experienced sellers are “over-represented” since they list more items. For example, the top quintile of sellers listed a full 66% of all auctions in the sample, compared to just 4% by the lowest quintile. For this reason the overall share of auctions ending between 5 and 8 PM, 34.5%, is closer to the 5th quintile than to the 1st.
a crowded environment. The fact that people tend to only receive (absolute) feedback about the actions they take, rather than relative feedback compared to the actions they did not take, has been long recognized as one of the major challenges for businesses and organizations to learn from experience (Russo & Schoemaker, 2002). 17

***Figure 4***

F. Effect of B/A on Probability of Sale

Prediction 2 states that auctions that end during periods of peak demand, and hence during the trough of the B/A, will have lower expected payoffs. This effect is predicted to be caused by lower expected price if all items are sold (during at least one time period) and by probability of sale if not all items are sold (also during at least one time period). This subsection evaluates the impact of the B/A on probability of sale, and the next one examines final price.

To measure the impact of the B/A at the time when an auction ends it is necessary to define a window of time for computing the relevant B/A. The results presented in this section were obtained defining a window of three hours, i.e. by assessing the impact of the B/A in the whole DVD market during the last 180 minutes of an auction, on that auction’s probability of sale. The results are robust to computing the B/A over the last 120 or 60 minutes.

Prediction 2 refers to the impact of predictable variation in B/A on seller revenue (i.e. of ending an auction at times of day when there are systematically less bids per auction). To test

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17 This is a fundamental selection bias problem often overlooked by economists. Firms know about the performance of products they launch, not of those they don’t, of the productivity of workers they hire, not of those they don’t, etc. Unless firms introduce (some) randomness into their decision processes, their experience simply cannot validate (or refute) the basis on which they make decisions. Non-catastrophically wrong decisions can survive abundant yet incomplete feedback. Market forces, on the other hand, will only drive suboptimal companies out of business under perfect competition, otherwise some firms will simply make less than maximal profits, but will not go bankrupt.
the prediction, therefore, it is important to exclude the influence of *contemporaneous* shocks of the B/A on the probability of sale. Even if the markets were in equilibrium, unanticipated shocks would lead to a positive ex-post relationship between B/A and payoffs; if more bidders happen to be online when an auction is ending, its probability of sale should go up.

To isolate contemporaneous shocks from the B/A, instead of using the actual B/A during the last 180 minutes of an auction’s clock as a predictor, the analyses were run using the *average* B/A, for the time of day when the auction ends, for all *other* days in the sample.

For example, if an auction ended at 8:45PM on Tuesday October 8th, rather than predicting the outcome of that auction with the B/A between 5:46PM and 8:45PM of October 8th, the average B/A between 5:46PM and 8:45PM from all other weekdays in October was used instead. This average ratio is referred to as B/A*. Obviously, an association between B/A* and ex-post payoffs cannot be caused by contemporaneous shocks. Because of slight differences in hourly traffic, B/A* was calculated separately for weekdays and weekend days.

In order to gain an intuitive sense of the relationship between B/A* and probability of sale, the subsample of 8,056 auctions was categorized into quintiles according to their B/A*, and probability of sale was compared across quintiles. The results are presented in Figure 5. Quintiles’ average probabilities were obtained from parameter estimates in a linear probability model with quintile dummies. The solid line corresponds to the parameter estimates from a regression which controls only for starting price, and the dotted line from one controlling for all movie and seller observables.

***Figure 5***

The figure shows that, consistent with prediction 2, auctions ending during hours of higher B/A* have a higher probability of being successful, going from 67% for auctions in the
lowest quintile, to 75% for those in the highest. The fact that the line which controls for observables is so close to the one that doesn’t, suggest that heterogeneity across auctions with different ending times is not what’s behind the impact of B/A*.

Table 3 presents the results from a logistic regression where auctions are the unit of analysis, the dependent variable is dichotomous, taking the value of 1 if the item was sold and 0 otherwise, and the key independent variable is the B/A*. Column 1 controls only for auction variables: starting price and duration (in days), column 2 adds movie controls and column 3, seller controls. Column 4 will be discussed later.

***Table 3***

Column 1 shows that auctions with lower starting prices and those lasting more days are more likely to be successful. Most importantly, in line with prediction 2 and with Figure 5, the coefficient for B/A* is positive and significant; auctions ending during hours of the day when there are systematically more bids per ending-auctions are more likely to be successful. The size of the coefficients drops when movie fixed effects and the dummy new (which takes the value of 1 if the item is described as “new”, “sealed” or “wrapped” and 0 otherwise) are incorporated into the regression in column 2, but it remains significant and does not drop much further after incorporating seller controls. Estimated at sample means the effect size (from column 3) is such that setting an auction to expire during the hour of peak demand, when B/A reaches its minimum, instead of the hour of trough demand, when B/A is at its highest, reduces the probability of sale by 9.6%.

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18 As was mentioned earlier, 28% of the sample is missing information on shipping charges and hence the regression does not control for shipping in order to avoid dropping an important part of the sample. If shipping is added to the regression (and the observations with missing information are dropped) the qualitative nature of the results remains unchanged.
Moderating impact of starting price.

The explanation proposed in this paper for the fact that auctions ending during peak demand hours have lower probability of sale is that: bidders bids last minute → ending-time influences who bids on a given auction → B/A when an auction ends impacts outcomes. From this mechanism it follows that the impact of B/A on auctions’ outcomes should be stronger for auctions that rely more heavily on last minute bidding. To further test the mechanism being proposed, therefore, it would be useful to assess whether the impact of B/A is stronger on auctions that are more dependant on last minute bidding.

Simonsohn and Ariely (2005) document that auctions with higher starting prices tend to receive their first bids significantly later during the auction period. Starting price, therefore, may be a useful variable to classify auctions that are more and less likely to be influenced by B/A.

Figure 6 shows the proportion of auctions receiving their first bid with just 60 minutes left in the auction, as a function of starting price. Note that the first bid is the most relevant one for this analysis, because it turns an unsold item into a sold one (recall that all items in the sample do not have a reserve price). The figure shows that indeed an auction’s starting price has a marked effect on the probability that it will receive its first bid late. No auction with a starting price of $0 received its first bid on the last hour, while 20% of auctions starting at $10 did.

*** Figure 6 ***

If the estimates from columns (1)-(3) in Table 3 are consistent with prediction 2 because of consequences of late-bidding, auctions with higher starting prices should exhibit a larger B/A* effect. To test this prediction the regression whose results are presented in Table 3 was estimated only for auctions starting at $5 or above. The results are reported in column 4; as predicted the point estimate for B/A* is noticeably larger. Estimated at sample means, the effect
size is such that setting an auction to expire during peak demand hours reduces the probability of sale by 14.3 %, compared to the 9.6% obtained from the whole sample.\textsuperscript{19}

As benchmarks, we can compare this effect size to those of other seller variables which have been previously studied, such as how long an auction lasts (see e.g. Lucking-Reiley, Bryan, Naghi, & Reeves, 2000) and seller reputation (see e.g. Resnick, Zeckhauser, Swanson & Lockwood (2006)).\textsuperscript{20} The predicted effect size of listing an item for seven instead of three days is 13.6%, and of increasing the seller’s rating in one standard deviation is 6.4%. The time-of-day effect, therefore, is of roughly the same magnitude as previously studied variables.

\textit{G. B/A* and Final Price}

The model predicts an impact of B/A* on final price only if in at least one market (i.e. hour of the day) all auctions are completed successfully; intuitively, higher demand should lead to higher prices only if the good has become scarce. The average probability of sale in the sample is 78% and hence the previously reported higher probability of sale during non-peak periods of 9.6% is unlikely to lead all items within a given hour to sell. Since few hours are likely to obtain selling rates of 100%, B/A* should have a weak, if any, impact on final price.

Table 4 presents the results from estimating regressions where auctions are the unit of analysis, the dependent variable is final price, and the key independent variable is B/A*. Final price of auctions is a complicated dependent variable because a final price is obtained only for auctions that result in a sale (it is a censored dependent variable). Conducting a Tobit regression, however, is not entirely appropriate either, among other reasons, because it assumes that the

\textsuperscript{19} I also assessed the moderating impact of starting price by adding an interaction term between starting price and B/A* to the specification of column 3. Consistent with the results from column 4, the point estimate for the interaction terms is positive with a \textit{p}<.0001.

\textsuperscript{20} Resnick et al. review 15 studies looking at the impact of reputation and report the results from their own field experiment where they randomize reputation across sellers.
censoring point does not affect the value of the latent variable, but prior research has shown that starting prices not only censor low value bids, but also influence the behavior of bidders with valuations above it (Simonsohn & Ariely, 2005). \(^{21}\)

Table 4 hence reports the results both from OLS and Tobit regressions. Although both point estimates are positive, the OLS one is not significant and the Tobit’s estimate is significant only at the 10% level. The point estimates indicate that setting an auction to end during the hour of highest B/A* instead of the lowest increases final price by 7.4 cents according to the OLS point estimates, and by 15 cents according to the Tobit estimates. Although the evidence is weak, to the extent that there is an impact of B/A* on final price, it is in the predicted direction: higher final prices during hours of lower aggregate demand.

***Table 4***

IV. Alternative Explanations

The bulk of this paper has presented analyses showing a disproportionate share of auctions ending during peak demand hours, leading the probability of sale to be lower during such hours. This evidence is consistent with the notion of competition neglect, i.e. that when sellers decide when to end their auctions they neglect the strategic decisions of their counterparts and hence choose based on what would be most profitable in the absence of competition. In this subsection three alternative explanations will be discussed: (i) unobserved heterogeneity across sellers ending their auctions at different times of day, (ii) differential listing costs throughout the day, and (iii) risk-seeking behavior on the part of sellers.

A. Unobserved Heterogeneity.

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\(^{21}\) One alternative would be to estimate a Heckman procedure, but there aren’t any obvious variables to be included in one regression and excluded from the other. I attempted to conduct such a procedure anyway, obtaining identification only from the functional form assumptions, but the estimation routine did not converge (proc qlim in SAS V9.1).
Like all field studies, this one suffers from the potential confound of unobserved heterogeneity. Unobserved heterogeneity across goods has arguably been reduced to a minimum by restricting the analysis to DVD movies, a commodity. Once fixed effects for movie title and a dummy for new vs. used are present, little remains to be known about the item being offered. *Sellers*, on the other hand, may differ in unobserved ways. It is possible that the higher probability of sale of off-peak auctions is due to the fact that (unobservably) superior sellers end their auctions at non-peak hours. 22

There are at least three reasons to doubt that unobservable seller heterogeneity is behind the results: (1) there is no theoretical justification for superior sellers to disproportionately end their auctions during off-peak hours, (2) sellers’ unobserved heterogeneity is incapable of explaining the evidence consistent with prediction 1 (i.e. with the disproportionate share of sellers ending their auctions during peak demand hours), and (3) unobserved heterogeneity cannot account for the larger coefficient of B/A* for auctions with higher starting prices (i.e. column 4 in Table 3). Despite its ex-ante lack of plausibility, is still useful to address empirically the potential role that unobserved seller heterogeneity may be playing.

Although seller fixed effects could address the potential problem of heterogeneity, they are not a feasible solution, as there are too few observations per seller (1,473 of the 2,404 sellers have just one observation in the subsample). A viable alternative consists of proxying for unobservable heterogeneity with observable variation. Given that unobservable seller heterogeneity is only a concern if it correlates with the ending times they choose for their auctions, it makes sense to use sellers’ average choice of ending time as a proxy for such

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22 Sellers could be ‘superior’ in a variety of ways, such as in their ability to promote their auction through catchy descriptions or of being able to provide more expedient deliveries depending on their geographical location.
heterogeneity; although it certainly will not capture all aspects of heterogeneity, it should capture quite well that which is problematic for the interpretation of the previous results.

To this end, to the regression estimating the impact of B/A* on an auction’s probability of sale (column 3 of Table 3) two additional predictors were added: sellers’ *average* B/A* across all of their auctions, and sellers’ standard deviation in the ending time of their auctions (both computed using the full sample of 518,064 auctions).

If the time at which an auction ends proxies for some unobserved characteristic of the seller listing it, then *average* B/A* across all auctions of that seller should be an even better proxy (less noisy) and hence also be a significant predictor of probability of sale. Furthermore, once seller’s average B/A* is included in the probability of sale regression, the estimated impact of an auction’s own B/A* should be heavily attenuated if not eliminated altogether.

Similarly, since sellers with lower variation in the ending time of their auctions are more likely to end them during peak demand hours (see Figure 3), seller’s variation in ending times may also proxy for the unobserved heterogeneity that lead sellers to choose certain times rather than others, and hence we may also expect sellers’ standard deviation in ending time to predict the probability of sale of individual auctions, and to diminish the estimated impact of an auction’s B/A*.

***Table 5***

The results of these regressions are presented on Table 5. Since sellers with just 1 or 2 auctions in all of October were dropped, sample size was reduced to 7,413 auctions. The table reports only the point estimates for the key variables although all control variables present in Table 3 were included.
Column 1 corresponds to the same specification as column 3 in Table 3 (the point estimate for B/A* are not identical because Table 5 excludes sellers with just one or two auctions). Column 2 adds the seller’s average B/A*. Contrary to the unobserved heterogeneity explanation, the point estimate -though positive- is far from significant (p = .67). Although the coefficient of interest, B/A*, drops in magnitude, it remains positive and significant.

Column 3 controls for the seller’s standard deviation in ending time (in minutes). The point estimate of standard deviation is also not significant (p = .15), and the point estimate of B/A* is barely influenced. Similar results are obtained if average B/A* and variation in ending times for the seller are simultaneously included (column 4). These results cast further doubt on the proposition that an auction’s ending time predicts auctions outcomes because of omitted seller heterogeneity.

B. Listing costs.

Recall that, unless a 10-cent fee is paid, auctions’ ending time coincides with the time of day at which the seller listed the item. Considering that the amount of time required for listing items on eBay is probably greater than the time required for bidding on them, sellers may be more constrained than bidders in their ability to engage on eBay activities while at work. This could lead sellers to be more likely than bidders to participate on eBay after work and hence to a greater clustering of auctions during the early evening. In other words, the more pronounced peak of auctions may occur not because sellers are failing to take into account the behavior of other sellers, but because the listing costs involved in listing items at non-peak hours are proportionally larger for sellers than for buyers.

Since listing cost differentials are hypothesized to arise from listing items while at work versus while at home, sellers who are stores and sellers listing on weekends should face smaller
(if any) hourly cost differentials, and hence, should exhibit a less pronounced peak. Similarly, listings for more expensive items (e.g. bundles of multiple DVD movies) involve larger benefits in terms of choosing “the right” ending time, and since the amount of time required for listing an item is independent of the item’s value, listings of more expensive items should also exhibit a less pronounced peak. To test these the plausibility of the listing-costs explanation, the B/A ratio during peak demand hours was computed for the aforementioned subsets of auctions and compared to the sample overall. The results are presented on Table 6.

***Table 6 ***

For example, the first row in Table 6 shows that for the sample as a whole, with 517,064 auctions, the B/A during the peak demand period is 0.73 (25% of bids divided by 34.5% of auctions). Contrary to the listing-costs explanation, the table shows that stores, weekend listers and listings with starting prices above $30 & $60 show a B/A almost identical (ranging between .72 and .78).

Another prediction from the listing-costs explanation is that sellers who paid the scheduling fee (the fee that allows a seller to deviate from the default of having an auction end at the same time of day when it is listed), should show no excessive entry during peak demand hours. As was shown earlier, and as is highlighted in the last row of Table 6, this subgroup of sellers engages in more rather than less peak-listing. In sum, none of the predictions arising from the listing cost story find support in the data.

C. Risk-seeking.

Finally, the greater clustering of auctions around peak demand hours may be the consequence of risk-seeking sellers who accept a lower average payoff during those hours in exchange of an increased probability of obtaining an extremely positive outcome.
This explanation also lacks ex-ante plausibility: we have no reason to expect neither that sellers are risk seeking, nor that auctions obtain higher variance in their final prices during peak demand hours. It is nevertheless useful to test whether this alternative explanation could account for the data. One way to test if the variance in final prices is higher during peak demand hours is to examine whether auctions ending at those times are more likely to obtain a price above a certain threshold.

To this end, a regression was estimated where each auction is the unit of analysis, the dependent variable is dichotomous taking the value of 1 if the auction obtained a final price above a certain threshold and 0 otherwise, and the key predictor is $B/A^*$. If auctions’ final prices have greater variance during peak demand hours, $B/A^*$ should be negatively correlated with the probability of an auction obtaining an arbitrarily high price.

This regression was estimated controlling for all observables used in prior regressions, and using as the arbitrary thresholds prices that correspond to the 60%, 70%, 80% and 90% percentile of final prices in the sample. In other words, these regressions estimate the relationship between $B/A^*$ during the last 180 minutes of an auction, and the probability that it obtains a final price above these percentiles. Contrary to the risk seeking explanation, the coefficient of $B/A^*$ is positive and significant for the first two thresholds, and positive but not significant for the last two thresholds (not reported). There is hence no evidence that auctions during peak demand hours have a higher likelihood of obtaining extremely high prices and hence risk-seeking could not explain the results.

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23 It is unclear how to treat unsold items for testing the risk-seeking story. If unsold items are dropped from the regressions instead of being counted as not achieving the threshold (sellers, after all, keep unsold items), the results remain qualitatively unchanged: for all four thresholds the point estimate of $B/A^*$ is positive, though only significant now for the first threshold.
V. Content analysis of eBay books

Section III provided evidence consistent with competition neglect among eBay sellers, while section IV ruled out alternative explanations for that evidence. This section, in turn, provides evidence that supports the notion that sellers not only behave as if they engaged in competition neglect, but that they actually and literally do ignore the impact of the actions of other sellers on the profitability of the actions they choose. In particular, this section analyzes the content of multiple books where eBay “experts” give advice to their readers about how to sell on eBay, and examines what their advice with respect to ending time is.

A. Books Sample

The growing popularity of eBay has lead to a proliferation of publications dedicated to help both buyers and sellers participate on it. In February of 2006, for example, a search on Amazon.com for the terms “eBay” and “sell” returned 49 different books, all apparently consisting of seller guides. The recommendations printed in these books can safely be assumed to consist of an upper bound of the typical eBay seller’s sophistication, since these are written by eBay “experts.” If people writing books about eBay fail to take into account how the actions of other sellers influence the profitability of different ending times, it seems particularly plausible that eBay sellers in general fail to do so as well.

In order to systematically analyze the content of eBay books, a research assistant visited the campus bookstore and the largest local Barnes and Noble bookstore and collected information from all eBay books in stock. In order to minimize subjectivity in the interpretation of their content, the research assistant remained blind to the hypothesis for the duration of the data collection. In addition, the research assistant was asked to collect data not only on ending
time, but also on starting price and shipping charges, providing further distance between the hypothesis being tested and the individual collecting the data.

**B. Results**

Table 7 summarizes the recommendations for ending time contained in these books. The first two columns indicate the ISBN and title of the books. The last column provides a very brief summary of the ending time recommendation itself, the third column indicates the key rationale behind the recommendation and the fourth column the corresponding level of sophistication (level 0,1 or 2).

Books not mentioning ending time at all, or failing to consider both demand (distribution of bids through the day) and supply (number of other auctions ending) are coded as giving level-0 recommendations. Those which mention only aggregate demand are coded as level-1 and those that mention both supply and demand as level-2s.

*** Table 7 ***

A total of 26 different books were included in the sample, they consist of all eBay books found at the two bookstores (no selection rule was used). Out of these 26 books, 8 make no ending time recommendation or propose that ending time does not matter, and hence are coded as level-0s. 14 books recommend ending auctions during periods of peak demand and are hence coded as level-1 recommendation (incidentally, most of them identify a peak period that overlaps with that observed in the DVD sample). Finally, only two books mention the ending time decisions of other sellers as a factor (i.e. do not neglect competition). They both recommend ending auctions during off-peak hours and are hence classified as level-2 recommendations.
In sum, the analysis of eBay books was consistent with the competition neglect story. Online sellers, it seems, not only behave as if they ignored the decisions of other sellers, they do in fact ignore them.

VI. Conclusions

Based on the experimental literature documenting competition neglect, i.e. players’ tendency to behave as if they systematically underestimated the impact of their competitors’ behavior on their payoffs, it was predicted that sellers would over-supply high-demand markets. This hypothesis was tested analyzing auctions’ ending-time decisions of eBay sellers. As predicted, a disproportionate fraction of sellers end their auctions during peak bidding hours, leading auctions that end during such hours to have lower probability of sale. Interestingly, this excessive entry seems to be driven by the subset of sellers who intentionally choose ending times, rather than by those who do so mindlessly.

Studying the prediction of excess entry into high demand markets within the context of the timing of auctions for a commodity has two important advantages. The first is that, unlike most other settings, in this one markets differ only on their demand levels, making comparisons of outcomes across markets much easier to interpret; there are no potential confounds of entry costs, required expertise, uncertainty, etc. The second advantage is that, again unlike most other settings, by studying the performance of a commodity, counterfactual outcomes for items offered in one market are available from other markets, and hence one can estimate with a high degree of certainty what a seller would have obtained had she entered a different market.

Although eBay is an ideal setting for the present study, it seems likely that the documented pattern is present in many other industries; future research should attempt to
replicate these findings elsewhere. Intuitively, this excessive entry pattern is more likely to occur in situations where sellers do not receive feedback about the profitability of lower demand markets. This would occur, for example, in settings where decisions are made by independent small sellers who observe one or just a few (of their own) entry decisions, as is the case with owners of independent restaurants or with people choosing what specific human capital to invest on or where to supply it.

It is also likely to occur in industries where a high-demand market is so focal, that even large sellers will not have experimented with smaller markets, as seems to be the case, according to (Einav, forthcoming), with the movie industry’s reluctance to launch blockbuster films on non-peak times of year (if nobody does it, there is no feedback to learn from).

Sellers’ tendency to oversupply high demand markets may also be one of the forces behind the long-standing paradox of why retail prices drop during peak demand periods (e.g. Turkeys being cheaper around Thanksgiving). Existing explanations are that (i) demand elasticities increase during high demand periods (Bils, 1989; Warner & Barsky, 1995), (ii) stores lower high-demand products’ prices to use them as loss-leaders (Chevalier, Kashyap, & Rossi, 2003; Lal & Matutes, 1994) and (iii) that seller collusion is more difficult during peak demand periods (Borenstein & Shepard, 1996; Rotemberg & Saloner, 1986).

Competition neglect provides an additional possible mechanism: sellers may simply over-supply markets during high demand period. This could occur, for example, if smaller/seasonal producers produce only during the peak periods (for example, lesser known Matza brands are only available during Passover) or if larger sellers themselves overproduced.

At a bigger picture level, the results from this paper demonstrate that psychological insights, which have become more and more common for economists to use in our understanding
of consumer behavior, can also help us understand firm behavior. Firms, after all, do not make
decisions, people who work in them do. Just because stakes are often higher inside the firm we
should not expect people to get it right. People have been documented to fall prey to biases
when making high stake individual decisions such as how much to spend in housing (Simonsohn
& Loewenstein, 2006), how much to save for retirement (Madrian & Shea, 2001) or whether to
take up a consumption loan (Bertrand, Karlan, Mullainathan, Shafir, & Zinman, 2005). It seems
reasonable to expect that they will also fall prey to biases when making decisions (big and small)
inside organizations.

As economists we tend to assume that firms cannot make systematic mistakes because
markets work to eliminate any deviation from optimality. This common assumption is not quite
correct. A firm can very well subsist with negative economic profits (i.e. once opportunity costs
are taken into account) as long as it has accounting profits (i.e. if it covers all its actual costs).
Indeed, a non-rational firm could run a rational one out of business if the owners of the former
were willing to tolerate lower than maximum profits while those of the latter were not.

In addition, even if market forces were strong enough to correct the bias, the process by
which such correction is attained is likely to be of interest to economists. For example, if as it is
speculated above, restaurant owners do tend to disproportionately enter into high demand
markets, then market forces are likely to push at least part of the excessive number of restaurants
out of business. If we can better understand business failures by using psychological insights
like competition neglect there is little reason not to.

Although there has been some interest in the part of behavioral economists to introduce
psychology into our understanding of firm behavior, such attempts have mostly focused on
understanding how perfectly optimal decisions of firms best respond to the suboptimal behavior
of consumers. For example, DellaVigna and Malmendier (forthcoming) look at how gyms exploit their customers’ hyperbolic discounting, Gabaix and Laibson (Forthcoming) at how companies hide expensive attributes from myopic consumers, and Simonsohn and Ariely (2005) at how bidders’ non-rational herding leads sellers to lower auctions’ starting prices.

The findings from this paper show that we can further improve our understanding of firm behavior by relaxing the assumption that the decisions people make inside firms are as rational as those we used to incorrectly assume they made outside of them.
Table 1. Payoffs ($\pi_i$) associated with entering market $i$ as a function of the number of sellers ($S_{p_{s,i}}$) and of buyers ($B_{p_{b,i}}$) entering $i$

<table>
<thead>
<tr>
<th>Case</th>
<th>Number of buyers and sellers entering $i$</th>
<th>$E[\pi_i(B_{p_{b,i}}, S_{p_{s,i}})]$</th>
<th>$\frac{\partial E[\pi_i]}{\partial p_{s,i}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i)</td>
<td>$B_{p_{b,i}} \geq 2S_{p_{s,i}}$</td>
<td>$v$</td>
<td>0</td>
</tr>
<tr>
<td>(ii)</td>
<td>$B_{p_{b,i}} &lt; 2S_{p_{s,i}}$ and $S_{p_{s,i}} \leq B_{p_{b,i}}$</td>
<td>$v\left(\frac{B_{p_{b,i}} - S_{p_{s,i}}}{S_{p_{s,i}}}</td>
<td></td>
</tr>
</tbody>
</table><p>ight) + c\left(1 - \frac{B_{p_{b,i}} - S_{p_{s,i}}}{S_{p_{s,i}}}\right)$ | $(c - v)\frac{B_{p_{b,i}}}{S_{p_{s,i}}^2} &lt; 0$ |
| (iii)| $S_{p_{s,i}} &gt; B_{p_{b,i}}$             | $c\frac{B_{p_{b,i}}}{S_{p_{s,i}}}$ | $-c\frac{B_{p_{b,i}}}{S_{p_{s,i}}^2} &lt; 0$ |</p>
Table 2. Descriptive Statistics (for subsample of 8,056 auctions)

<table>
<thead>
<tr>
<th></th>
<th>Final price of sold items</th>
<th>Duration of auction in days</th>
<th>Seller Rating&lt;sup&gt;a,b&lt;/sup&gt;</th>
<th>Total number of auctions by seller Jan-Sep 2002&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Starting Price received (per auction)</th>
<th># of Bids</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$10.31</td>
<td>5.36</td>
<td>747.8</td>
<td>171.9</td>
<td>$6.31</td>
<td>4.44</td>
</tr>
<tr>
<td>Median</td>
<td>$10.04</td>
<td>5.00</td>
<td>177.0</td>
<td>6.0</td>
<td>$6.99</td>
<td>3.00</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>$3.01</td>
<td>2.03</td>
<td>2,692.7</td>
<td>1,871.9</td>
<td>$3.79</td>
<td>4.32</td>
</tr>
</tbody>
</table>

<sup>a</sup> Seller rating is the net number of positive (+1) and negative (-1) reviews by buyers.

<sup>b</sup> Weighted average assigning each seller equal weight.
Table 3. Influence of Bids/Auctions ratio when auction ends (B/A*) on probability of sale (Logit Regression)

Dependent Variable: \(Y=1\) if item was sold, 0 otherwise.

<table>
<thead>
<tr>
<th>(1) Only auction controls</th>
<th>(2) Adds movie controls</th>
<th>(3) Adds seller controls</th>
<th>(4) Only auctions starting at $5 or higher</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td>3.006***</td>
<td>4.743***</td>
<td>4.039***</td>
</tr>
<tr>
<td>(0.176)</td>
<td>(0.337)</td>
<td>(0.418)</td>
<td>(0.370)</td>
</tr>
<tr>
<td>Bids/Auctions ratio (B/A*) last 180 minutes(^a)</td>
<td>0.636***</td>
<td>0.511***</td>
<td>0.490***</td>
</tr>
<tr>
<td>(0.110)</td>
<td>(0.149)</td>
<td>(0.148)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Starting Price</td>
<td>-0.370***</td>
<td>-0.530***</td>
<td>-0.535***</td>
</tr>
<tr>
<td>(0.013)</td>
<td>(0.031)</td>
<td>(0.031)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Duration of auction (days)</td>
<td>0.099***</td>
<td>0.216***</td>
<td>0.188***</td>
</tr>
<tr>
<td>(0.016)</td>
<td>(0.031)</td>
<td>(0.032)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>&quot;New&quot; (1 if item is new, 0 otherwise)</td>
<td>--</td>
<td>0.429**</td>
<td>0.409**</td>
</tr>
<tr>
<td>--</td>
<td>(0.189)</td>
<td>(0.186)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Log(seller rating)</td>
<td>--</td>
<td>--</td>
<td>0.210***</td>
</tr>
<tr>
<td>--</td>
<td>--</td>
<td>(0.049)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Log(# DVDs posted by seller Jan-Oct 2002)</td>
<td>--</td>
<td>--</td>
<td>-0.065*</td>
</tr>
<tr>
<td>--</td>
<td>--</td>
<td>(0.038)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Store Dummy (^b)</td>
<td>--</td>
<td>--</td>
<td>-0.103</td>
</tr>
<tr>
<td>--</td>
<td>--</td>
<td>(0.253)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>Movie Title Fixed Effects (DF=53)(^c)</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Pseudo R(^2)</td>
<td>0.204</td>
<td>0.355</td>
<td>0.360</td>
</tr>
<tr>
<td>Number of observations</td>
<td>8,056</td>
<td>8,056</td>
<td>8,056</td>
</tr>
</tbody>
</table>

Notes:

Standard errors (clustered by seller) reported below parameter estimates.

\(*\), **, *** indicates significant at the 10%, 5% and 1% level respectively.

\(B/A^*\) corresponds to the average bids/auctions ratio for the last 180 minutes of the auction, for all other days in October 2002 (i.e. excluding the day on which the auction actually ends).

\(^b\) Store dummy equals 1 if the seller has a contractual agreement with eBay, 0 otherwise.

\(^c\) There are 54 movie titles in the sample.
Table 4. Influence of Bids/Auctions ratio when auction ends \((B/A^*)\) on price

Dependent Variable: final price (in dollars)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technique</td>
<td>OLS</td>
<td>Tobit</td>
</tr>
<tr>
<td>Intercept</td>
<td>9.290**</td>
<td>8.889***</td>
</tr>
<tr>
<td></td>
<td>(0.284)</td>
<td>(0.335)</td>
</tr>
<tr>
<td>Bids/Auctions ratio ((B/A^*)) last 180 minutes(^a)</td>
<td>0.063</td>
<td>0.271*</td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td>(0.153)</td>
</tr>
<tr>
<td>Duration of auction (in days)</td>
<td>0.115**</td>
<td>0.143***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Starting-price</td>
<td>-0.274**</td>
<td>-0.232***</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Starting-price squared</td>
<td>0.030**</td>
<td>0.016***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Shipping</td>
<td>-0.180**</td>
<td>-0.186***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>&quot;New&quot; (1 if item is new, 0 otherwise)</td>
<td>0.674**</td>
<td>0.652***</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.093)</td>
</tr>
<tr>
<td>Log(seller rating)</td>
<td>0.129**</td>
<td>0.183***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Log(# DVDs posted by seller Jan-Oct 2002)</td>
<td>0.115**</td>
<td>0.094***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Store Dummy (^b)</td>
<td>-0.067**</td>
<td>-0.196***</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.176)</td>
</tr>
<tr>
<td>Movie Title Fixed Effects (DF=53)(^c)</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Sigma from Tobit Regression</td>
<td>--</td>
<td>2.566***</td>
</tr>
<tr>
<td></td>
<td>--</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>4,554</td>
<td>5,807</td>
</tr>
<tr>
<td>R(^2)/ Pseudo R(^2)</td>
<td>0.410</td>
<td>0.099</td>
</tr>
</tbody>
</table>

Standard errors (clustered by seller) reported below parameter estimates.

*,**,*** Indicate significance at the 10%, 5%, and 1% level respectively

\(^a\) \(B/A^*\) corresponds to the average bids/auctions ratio for the last 180 minutes of the auction

\(^b\) Store dummy equals 1 if the seller has a contractual agreement with eBay, 0 otherwise

\(^c\) There are 54 movie titles in the sample.
Table 5. Influence of B/A* on probability of sale (Logistic Regression), controlling for seller heterogeneity through proxies.

Dependent Variable: Y=1 if item was sold, 0 otherwise.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.226***</td>
<td>4.163***</td>
<td>4.208***</td>
<td>4.167***</td>
</tr>
<tr>
<td></td>
<td>(0.308)</td>
<td>(0.341)</td>
<td>(0.308)</td>
<td>(0.341)</td>
</tr>
<tr>
<td>Auction's B/A*</td>
<td>0.442***</td>
<td>0.386**</td>
<td>0.425***</td>
<td>0.388**</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.186)</td>
<td>(0.133)</td>
<td>(0.187)</td>
</tr>
<tr>
<td>Seller's Average B/A*</td>
<td>--</td>
<td>0.118</td>
<td>--</td>
<td>0.078</td>
</tr>
<tr>
<td></td>
<td>--</td>
<td>(0.278)</td>
<td>--</td>
<td>(0.279)</td>
</tr>
<tr>
<td>Standard deviation of seller's ending-times b</td>
<td>--</td>
<td>--</td>
<td>0.409</td>
<td>0.400</td>
</tr>
<tr>
<td></td>
<td>--</td>
<td>--</td>
<td>(0.287)</td>
<td>(0.288)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>7,413</td>
<td>7,413</td>
<td>7,413</td>
<td>7,413</td>
</tr>
<tr>
<td>Pseudo-R²</td>
<td>0.3675</td>
<td>0.3676</td>
<td>0.3678</td>
<td>0.3680</td>
</tr>
</tbody>
</table>

Notes:

All variables included as controls in table 3 are also included in these regressions.

Standard errors below parameter estimates.

Column (1) corresponds to the same specification as column (3) in table 4. Point estimates differ because sellers with 3 or less auctions are excluded from this specification.

*,**,*** indicates significant at the 10%, 5% and 1% level respectively.

a B/A* correspond to the average bids/auctions ratio for the last 180 minutes of the auction, for all other days in October 2002 (i.e. excluding the day on which the auction actually ends).

b Standard Deviation in minutes is divided by 1000 in order for the coefficient to be readable in the table.
<table>
<thead>
<tr>
<th>Subsample:</th>
<th>B/A during peak demand (5-8PM)</th>
<th>Number of Auctions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole sample</td>
<td>0.73</td>
<td>517,064</td>
</tr>
<tr>
<td>Seller owns a store</td>
<td>0.72</td>
<td>150,207</td>
</tr>
<tr>
<td>Listed during a weekend</td>
<td>0.75</td>
<td>143,466</td>
</tr>
<tr>
<td>Listing with starting price</td>
<td></td>
<td></td>
</tr>
<tr>
<td>above $30</td>
<td>0.78</td>
<td>33,848</td>
</tr>
<tr>
<td>above $60</td>
<td>0.75</td>
<td>9,608</td>
</tr>
<tr>
<td>Listed with scheduling-fee</td>
<td>0.52</td>
<td>8,112</td>
</tr>
<tr>
<td>ISBN</td>
<td>Book Title</td>
<td>Recommendation based on:</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------------------------------------------------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td>0-07-144569-2</td>
<td>How to sell Antiques and Collectibles on eBay</td>
<td>N/A</td>
</tr>
<tr>
<td>0-07-144519-8</td>
<td>Unleashing the Power of eBay</td>
<td>N/A</td>
</tr>
<tr>
<td>1-55257-333-9</td>
<td>The Complete Idiot's guide to starting an eBay Business</td>
<td>N/A</td>
</tr>
<tr>
<td>0-07-226252-4</td>
<td>Secrets of the eBay millionaires</td>
<td>N/A</td>
</tr>
<tr>
<td>0-07-226164-1</td>
<td>How to do Everything with your eBay Business</td>
<td>N/A</td>
</tr>
<tr>
<td>0-7697-3469-0</td>
<td>eBay to the Max</td>
<td>N/A</td>
</tr>
<tr>
<td>0-7607-7488-9</td>
<td>eBay in easy steps</td>
<td>Seller's convenience</td>
</tr>
<tr>
<td>0-06-076287-X</td>
<td>How to buy, sell profit on eBay</td>
<td>Doesn't matter</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-7645-6991-6</td>
<td>eBay Timesaving Techniques for Dummies</td>
<td>Aggregate demand</td>
</tr>
<tr>
<td>0-7697-3366-8</td>
<td>Making a Living from your eBay Business</td>
<td>Aggregate demand</td>
</tr>
<tr>
<td>0-684-86554-3</td>
<td>The Official eBay guide</td>
<td>Aggregate demand</td>
</tr>
<tr>
<td>0-672-32837-2</td>
<td>eBay in a Snap</td>
<td>Aggregate demand</td>
</tr>
<tr>
<td>0-7697-3290-4</td>
<td>Tricks of the eBay Masters</td>
<td>Aggregate demand</td>
</tr>
<tr>
<td>0-7645-6654-1</td>
<td>eBay for Dummies</td>
<td>Aggregate demand</td>
</tr>
</tbody>
</table>

*Table continues on next page.*
<table>
<thead>
<tr>
<th>ISBN</th>
<th>Book Title</th>
<th>Recommendation based on:</th>
<th>Implied level of sophistication</th>
<th>Specific recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-7697-3431-1</td>
<td>Absolute Beginner's Guide to eBay</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>End between 9-11pm EST</td>
</tr>
<tr>
<td>0-07-225869-1</td>
<td>eBay Power Seller Secrets</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>Between 6-9pm PST</td>
</tr>
<tr>
<td>0-321-25816-6</td>
<td>eBay Strategies</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>Timing your auctions to end during peak times will significantly improve traffic to your auctions, resulting in more bids, 8-12pm EST</td>
</tr>
<tr>
<td>0-8144-7289-3</td>
<td>eBay the Smart Way</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>Evening</td>
</tr>
<tr>
<td>0-07-225277-X</td>
<td>How to start and run an eBay Consignment Business</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>End on Sunday at 7pm PST to maximize your bidding activity. Saturday is also good.</td>
</tr>
<tr>
<td>0-471-71216-6</td>
<td>The eBay Millionaire</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>End when traffic is highest on eBay. Sunday evening is always a good time</td>
</tr>
<tr>
<td>0-7645-8833-3</td>
<td>The Unofficial Guide to Making Money on eBay</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>Between 7am and 7pm PST</td>
</tr>
<tr>
<td>0-7645-9727-2</td>
<td>Top 100 Simplified Tips &amp; Tricks</td>
<td>Aggregate demand</td>
<td>Level-1</td>
<td>End during evenings and weekends</td>
</tr>
<tr>
<td>0-7645-7612-7</td>
<td>The eBay myth-busters</td>
<td>Residual Demand</td>
<td>Level-2</td>
<td>Rare items sell anytime. If selling a fairly common item, high-traffic nights might be the absolute worst time to close (too much competition).</td>
</tr>
<tr>
<td>0-07-226236-2</td>
<td>Turn eBay Data into Dollars</td>
<td>Residual Demand</td>
<td>Level-2</td>
<td>You obviously want the largest number of bidders, but the number of sellers ending auctions for identical items dilutes the advantage.</td>
</tr>
<tr>
<td>0-07-225711-3</td>
<td>eBay your business</td>
<td>Seller's own data</td>
<td>Unclear</td>
<td>Depends on product and target market. Collect data for different times of day.</td>
</tr>
<tr>
<td>1-592-40092-2</td>
<td>The Official eBay Bible</td>
<td>Seller's own data</td>
<td>Unclear</td>
<td>Experiment with as many as you can, check listings that received the most bids.</td>
</tr>
</tbody>
</table>
Figure 1. Percentage of bids arriving towards the end of the auction

![Bar chart showing the percentage of bids arriving at different time points during the auction.](chart.png)

- **First bid**
- **All bids**
- **Winning bid**
Figure 2a. Hourly distribution of auctions ending and bids being placed

Figure 2b. Bids placed to auctions ending ratio (B/A) by hour.
Figure 3. Percentage of auctions ending during peak demand hours, by sellers’ decile of variation in ending times

Notes:
- Variation in ending-times in one half of the month used to predict ending-times in the other half.
- Average is computed with sellers as the unit of analysis.
Figure 4. Percentage of bids being placed and auctions ending between 5PM and 8PM as a function of experience (proxied by reputation rating of bidders and sellers respectively).
Figure 5. Probability of sale as a function of quintile of auction’s B/A*

Note: average probabilities of sale obtained from linear probability model with auctions as the unit of analysis. The averages correspond to the parameter estimates of the quintile dummies plus a constant. The estimates plotted on the dashed line were obtained controlling for all observables (all variables in Table 3).

Figure 6. Percentage of auctions receiving their first bid with 60 or less minutes left on their clock.
References


