

eBay's Crowded Evenings: Competition Neglect in Market Entry Decisions

Uri Simonsohn

The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19004, uws@wharton.upenn.edu

Do firms neglect competition when making entry decisions? This paper addresses this question analyzing the time of day at which eBay sellers set their auctions to end. Consistent with competition neglect, it is found that (i) a disproportionate share of auctions end during peak bidding hours, (ii) such hours exhibit lower selling rates and prices, and (iii) peak listing is more prevalent among sellers likely to have chosen ending time strategically, suggesting disproportionate entry is a mistake driven by bounded rationality rather than mindlessness. The results highlight the importance for marketing researchers of assessing rather than assuming the rationality of firm behavior.

Key words: market entry; marketing; competitive strategy; behavioral economics

History: Received August 4, 2009; accepted January 19, 2010, by Pradeep Chintagunta, marketing. Published online in *Articles in Advance* June 9, 2010.

1. Introduction

A basic premise of game theory is that agents choose among different courses of action, taking into account how the decisions of other agents influence their relative profitability. Firms, for example, are supposed to make entry and production decisions based on residual rather than aggregate demand, taking into account the impact of competitors on the demand they face.

This assumes that firms behave rationally. What may we expect if they were only boundedly rational? Abundant experimental and survey-based evidence has shown that people exhibit *competition neglect*, that is, that they tend to choose actions that maximize profits in the absence of competition, but that do not necessarily do so in its presence.

Moore and Cain (2007) find that too many subjects choose to compete on easy tasks, and too few on difficult ones (see also Radzevick and Moore 2008). Camerer and Lovo (1999) find that subjects do not adjust behavior sufficiently when competing against self-selected versus non-self-selected competitors. Real-world managers report seeing a small fraction of their actual competitors as rivals (Grisprud and Gronhaug 1985, Porac et al. 1989), and entrepreneurs report making entry decisions focusing primarily on variables under their own control, mostly ignoring competition (Moore et al. 2007).

In this paper, I propose and test a new prediction that arises from applying the notion of competition neglect to the decision firms face as to which of many possible markets to enter; if entrants do not

sufficiently take into account the impact of competition, they will tend to erroneously equalize residual demand with aggregate demand, *disproportionately entering markets with greater aggregate demand*. This would lead, for example, to too many restaurants opening in densely populated areas, to too many new radio stations for popular genres, and to too many gadgets being released shortly before Christmas.

Testing this prediction with nonexperimental data is problematic, of course, because markets that differ in aggregate demand also differ in other dimensions that are relevant for both entry and profitability, such as operational costs, barriers to entry, and uncertainty. Furthermore, the goods and services sold across markets that differ in aggregate demand are often heterogeneous themselves. In this paper, I examine this prediction of excessive entry into high-demand markets in a real market setting that is all but free of such confounds: the time of day at which eBay sellers choose to end their auctions.

Previous research has consistently documented that online auctions receive a high share of bids as they are about to end,¹ creating a relationship between an auction's ending time and the demand it faces. The fortune of an auction ending at 8 P.M. will tend to be determined by bidders who are online in the evening, whereas that of an auction ending at noon will be determined by morning bidders. In other words, as a consequence of last-minute bidding, eBay consists of multiple quasi-independent sequential markets that

¹For reviews, see §3 in Bajari and Hortacsu (2004) and §4 in Ockenfels et al. (2006).

differ almost exclusively on their demand levels. If sellers neglect competition, they will tend to *disproportionately* choose to end their auctions during the times of day when more bidders are online.

I test this prediction with data from 11,796 auctions for best-selling single-DVD movies (e.g., *Monsters Inc.*) and 3,177 auctions for frequently offered multiple-DVD bundles (e.g., the first season of the TV show *Friends*). Consistent with competition neglect, both supply (auctions ending) and demand (bids being placed) peak in the evening, but the peak of supply is significantly more pronounced than that of demand. For example, between 5:00 and 8:59 P.M., bidders place 25.0% of their bids, compared to the 37.6% of all auctions that end during such hours (see Figure 2 in §2.3). Various analyses suggest that the bidders' peak is exogenous with respect to the behavior of sellers (e.g., visits to Amazon.com have a very similar pattern and bidder experience is uncorrelated with time of day at which bids are placed).

Sellers' disproportionate entry has consequences: their profits are *lower* during peak bidding hours. An average seller listing her auction at around noon rather than around 8 P.M., for example, would increase her odds of selling a single DVD by 13 percentage points and increase its expected price by about 38¢ (a 4% increase). For a DVD bundle, the consequences would be a 5 percentage point increase in probability of sale and \$3.40 in final price (a 6% increase). Given how competitive the market for DVDs is, these price effects are likely to constitute a significant share of the profits sellers take home.²

I interpret such disproportionate entry into, and lower profits during, peak bidding hours as evidence that competition neglect influences both eBay sellers' decisions and market outcomes. The most plausible alternative explanation relies on listing costs. In particular, considering that eBay auctions end at the same time of day as when sellers list them, if *listing* during peak bidding hours is more convenient (less costly), then sellers may willingly accept a lower expected profit for listing at such times.

Several additional analyses suggest this explanation does not account for the excessive entry results. For example, sellers who pay a fee that allows them to change the default ending time of their auction, end a *higher* share of their auctions during the peak (48%) than sellers not paying the fee do (37%). Also, subsets

of sellers that should be less influenced by the convenience of early-evening listing, such as stores, sellers listing on a weekend, and sellers listing more expensive items, all end a similar share of their auctions during peak hours as the rest of sellers do.

Furthermore, collecting information from books giving advice to eBay sellers, I obtained anecdotal evidence that supports the competition neglect interpretation of the data. In particular, I found that of 26 books consulted, the vast majority making ending-time recommendations make them based on aggregate demand, fully neglecting the role of competition. The notable exceptions are two books that indicate that although peak hours are attractive because there are more consumers around, there are also more competitors, and so they advise their readers to avoid listing their items during the peak.

One concern with studying entry decisions with auction data is the question of whether eBay sellers are in fact firms who seek to maximize profits (rather than individuals, say, getting rid of unwanted items). This issue is discussed in some detail in the Conclusions section, but it is worth mentioning here that a sizeable share of items in the data are listed by large sellers and that, furthermore, such sellers are more rather than less likely to excessively end their auctions during the peak-demand period. In fact, additional analyses suggest that the excessive entry into peak bidding hours is driven primarily by professional sellers, not individuals.

In documenting sellers' failure to take into account relevant factors when making decisions, this paper is related to a growing empirical literature studying inattention. Recent research, for example, has shown evidence of inattention to nonsaliently displayed prices (Hossain and Morgan 2006, Lee and Malmendier 2010, Simonsohn and Ariely 2008), to information that competes with attention grabbing or abundant information (DellaVigna and Pollet 2009, Eisensee and Strömberg 2007, Hirshleifer et al. 2009), and to future events occurring beyond immediate planning horizons (Che et al. 2007, DellaVigna and Pollet 2007).

More broadly, it is also related to a growing literature that employs field data to study psychological findings that are relevant for marketing researchers, such as the prominence effect (Hsee et al. 2008), contrast effects (Simonsohn 2006, Simonsohn and Loewenstein 2006), and the should/want distinction for consumer goods (Milkman et al. 2009). For a review of the closely related literature of behavioral economics with field data, see DellaVigna (2009). Finally, in studying bounded rationality in a market entry setting, this paper is related to Goldfarb and Xiao (2010) and Goldfarb and Yang (2009), who apply structural bounded rationality models to market entry

² The first version of this paper contained only the single-DVD sample and found an effect only on probability of sale. While working on a separate paper (Simonsohn 2010), I improved the algorithm to identify eBay items based on sellers' descriptions. After cleaning the data set with this new algorithm, the price effect became significant. For robustness, I created the DVD-bundles sample, replicating the effect on prices.

Table 1 Descriptive Statistics

| | Final price of sold items (\$) | No. of bids received (per auction) | Percentage sold (%) | Seller rating | Starting price (\$) | Duration of auction in days | Shipping charges | Percentage with reserve price (%) | Percentage offered by stores (%) |
|--------------------------------------|--------------------------------------|--|------------------------|------------------|------------------------|-----------------------------------|---------------------|---|--|
| Single-DVDs sample ($N = 11,796$) | | | | | | | | | |
| Mean | 10.16 | 4.68 | 70.8 | 1,819 | 7.23 | 4.78 | 3.60 | 0.9 | 13.9 |
| Median | 9.99 | 3.00 | — | 495 | 8.00 | 5.00 | 3.50 | — | — |
| Standard deviation | 2.80 | 3.99 | — | 3,969 | 4.05 | 2.17 | 1.10 | — | — |
| Multiple-DVDs sample ($N = 3,177$) | | | | | | | | | |
| Mean | 55.92 | 9.82 | 89.6 | 1,511 | 21.80 | 4.63 | 6.40 | 7.3 | 11.0 |
| Median | 55.00 | 10.00 | — | 349 | 9.99 | 5.00 | 6.00 | — | — |
| Standard deviation | 26.87 | 6.30 | — | 3,184 | 24.51 | 2.19 | 2.26 | — | — |

Note. Average final prices and number of bids exclude unsold items.

decisions and study the correlates of imputed strategicness in entry behavior across firms.

2. Data Description and the Disproportionate Entry Pattern

Although many eBay 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. Over half the items in the sample used in this paper, for example, were listed by sellers listing at least 300 DVDs during the first nine months of 2002.

By default, auctions end at the same time of day as when sellers list them. For example, suppose a seller sets up a three-day auction at 10:17 A.M. on Monday; this auction would start immediately and end on Thursday at 10:17 A.M. Sellers have an option to pay a 10¢ scheduling fee that allows them to start (and, hence, end) their auction at a time other than when they list it.³

2.1. The Data Set

2.1.1. Data Description. The raw data set contains information on over 500,000 auctions, and their corresponding over 1.2 million bids, encompassing all auctions taking place in October of 2002 in the DVD movie category. Because eBay does not employ product codes that uniquely identify items being auctioned (e.g., UPCs or ISBNs), bidders and researchers must rely on sellers' descriptions of their items to identify the products being auctioned. For this reason I conducted an item identification process, described in detail in Appendix A, to create two subsamples. One contains single-DVD movies that were listed as weekly best sellers at IMDB.com at least once during the 10 weeks preceding the sampling period (e.g., the

film *A Beautiful Mind*), and the other contains common multiple-DVD packs (e.g., the first season of the TV show *24*).⁴

2.1.2. Descriptive Statistics. Table 1 shows overall means, medians, and standard deviations for variables used in the analyses that follow, tabulated separately for both subsamples. Auctions for single DVDs have lower prices, probabilities of sale, and numbers of bids than multiple-DVD auctions.

The samples combined contain auctions from 4,513 different sellers. The single seller with the greatest market share offered about 2.4% of all auctions, and the largest 10 sellers combined just under 16%; eBay auctions for DVDs are not a highly concentrated market.

2.2. Late Bidding

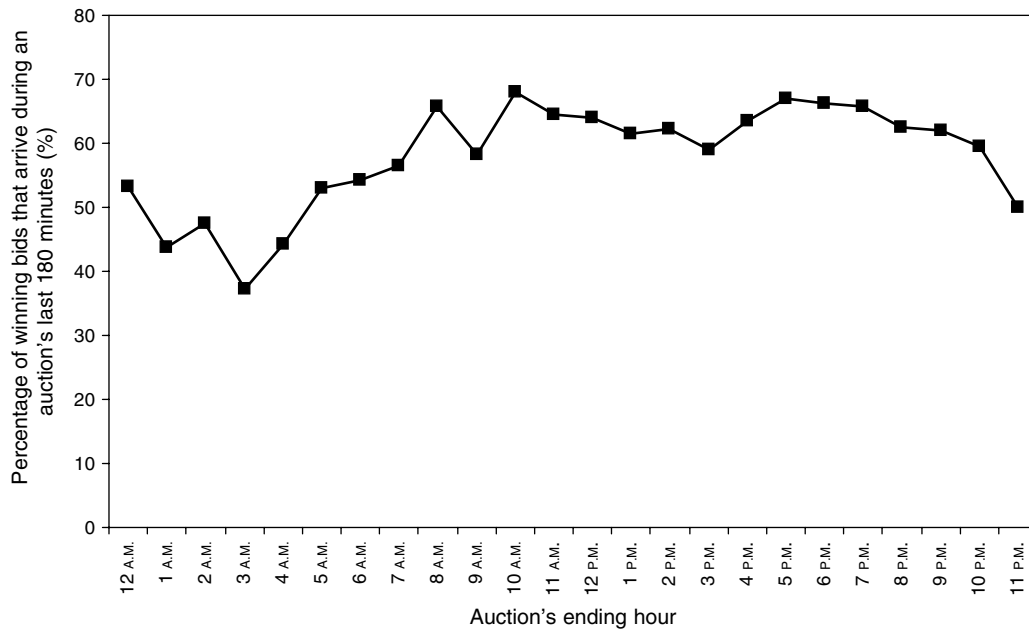
As mentioned in the introduction, a number of papers have shown that a substantial share of bids arrive as auctions are about to end. The auctions in this sample are no exception. Over 60% of winning bids arrive with less than three hours left in the auction, and 18% of them during an auction's last minute.

Given that a key premise in this paper is that last-minute bidding creates a link between an auction's ending time and the bidders that end up determining its fate, it is necessary to assess the prevalence of last-minute bidding through the day. Figure 1 plots the percentage of auctions, by hour at which they end, that received their winning bid during their last 180 minutes (auctions not resulting in a sale are excluded from the figure). The figure shows that late bidding is relatively stable through the day. Early auctions do show somewhat less late bidding, but fewer than 8% of auctions depicted in Figure 1 end before

³ All times reported in this paper are Pacific standard time.

⁴ The excessive entry pattern is observed not only in these subsamples of relatively high-frequency items but also in the overall data set of DVD auctions. In particular, in the full data set, 25% of bids are placed during the peak, but 34.5% of all auctions end during such hours.

Figure 1 Extent of Late Bidding by Hour of Day



Notes. The figure shows the fraction of winning bids arriving within an auction's last 180 minutes. There are 11,531 observations depicted in the figure (auctions receiving zero bids are excluded). Less than 7% of auctions depicted in the figure end between 12 A.M. and 7 A.M.

7 A.M. In sum, Figure 1 suggests that indeed an auction's ending time is likely to strongly influence the bidders it faces, and that such a link is more or less stable through the day.

2.3. Timing of Bids and Auctions

Figure 2 plots the percentage of daily auctions ending, and of bids placed, by hour. Multiple bids by the same bidder are excluded, keeping only a bidder's last bid (this is the time when the bid was actually placed, excluding automatic revisions by eBay's proxy bidding system).

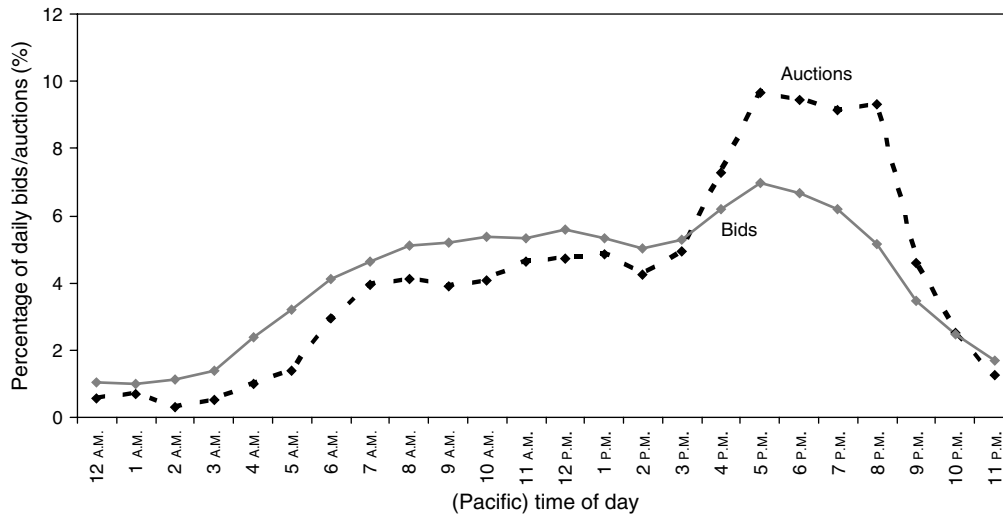
The figure shows that the frequency of new bids increases consistently through the day until reaching a peak at around 5 P.M., and then it slowly declines until the end of the day. Auctions show a qualitatively similar pattern.

Consistent with competition neglect, however, where sellers would choose the ending time of their auction at least partially ignoring competition, the auction's peak is much more pronounced than that of bids. Between 5:00 P.M. and 8:59 P.M., bidders place 25% of their bids, whereas sellers set 37.6% of their auctions to end. In other words, during the peak bidding hours, we observe roughly 50% more auctions than we would expect to observe if entry was proportional to demand. The greater fraction of auctions taking place during the peak than of bids being placed during such hours is, not surprisingly given the number of observations involved, statistically significant: $Z = 28.29$, $p < 0.0001$.

The hourly ratio of the percentage of auctions ending to the percentage of bids being placed provides an intuitive sense of how seller saturated different times of the day are. Figure 3 displays how this ratio changes through the day (with standard error (SE) computed via the delta method). At 8 P.M., for example, the most saturated hour in the sample, the ratio of the percentage of daily auction endings to the percentage of daily bids being placed is 1.79, compared to 0.84 at noon. This means that there are more than twice as many auctions per bid at 8 P.M. as there are at 12 P.M. To assess the statistical significance of the negative association between aggregate demand and residual demand, I estimated a regression using one observation per hour (i.e., $N = 24$), with the *auctions-to-bids* (A/B) ratio during that hour as the dependent variable and the share of daily bids placed during such hours as the sole predictor. In line with Figures 2 and 3, the estimated relationship is positive and significant ($\beta = 0.131$, $SE = 0.031$, $p < 0.01$).⁵

⁵ As pointed out by a referee, each observation in this regression is a "generated regressor" because they are hourly averages across the 31 days in the sample, but the sampling error in such averages is ignored in the regression. One way around this problem is to estimate the regression with the full set of 744 hours in the month as observations. With this specification, the qualitative nature of the results does not change ($\beta = 0.107$, $p < 0.001$). A two-stage estimator where in the first stage the percentage of daily bids is instrumented with hour dummies also leads to similar results ($\beta = 0.106$, $p < 0.001$).

Figure 2 Percentage of Daily Auctions Ending, and Daily Bids Placed, by Hour



Notes. The figure depicts the percentage of auctions in the single- and multiple-DVD samples combined ($N = 14,973$) ending at each hour of the day and the percentage of bids placed by hour ($N = 44,735$). Multiple bids by the same bidder on the same auction are excluded, keeping only a bidder's last bid.

2.4. Are the Peaks Strategic?

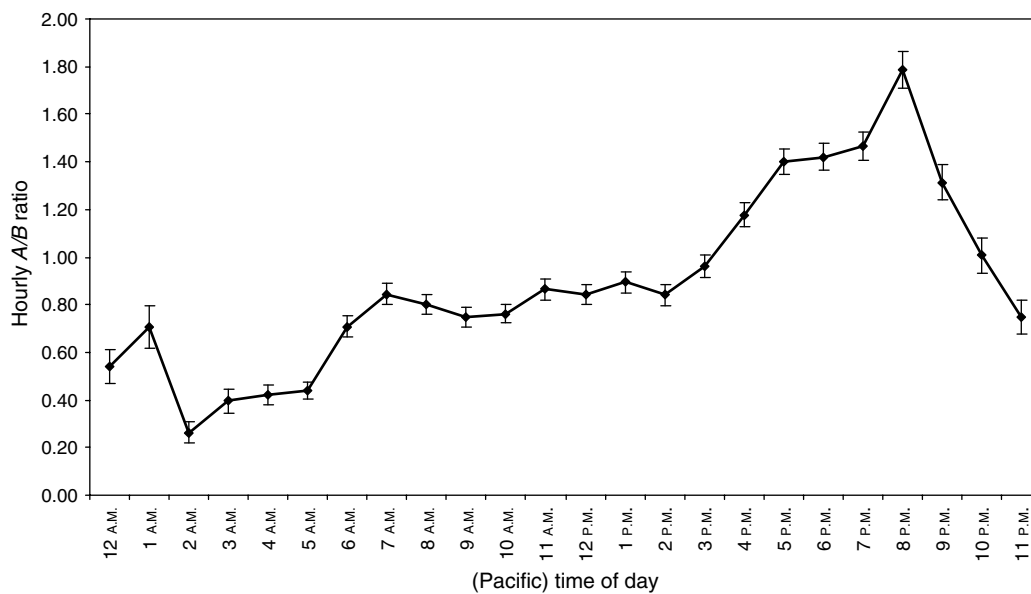
This paper studies how sellers respond to daily variation in demand, assuming that the timing of bids is exogenous. In what follows I first assess the validity of this premise and then look more closely at how strategic seller behavior is.

2.4.1. Demand's Peak. One way to assess if the actions of sellers influence the time of day at which bidders participate on eBay is to compare the timing of eBay bids through the day to the distribution of

visits to other shopping-related websites, where time plays no strategic role.

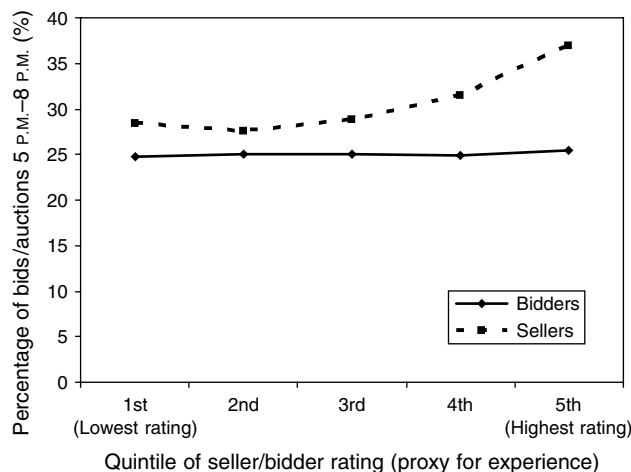
To conduct this comparison, I obtained data from comScore Inc., a panel of 2,000,000 Internet users. In particular, I downloaded data from a random sample of 100,000 users, available from Wharton Research Data Services (<http://wrds.wharton.upenn.edu>), and computed the percentage of daily visits to Amazon.com by hour (employing data also from October of 2002). According to these data, 25.9% of

Figure 3 Hourly Ratio of Percentage of Auctions Ending over Percentage of Bids Placed



Notes. The figure depicts the ratio of the percentage of auctions in the single- and multiple-DVD samples combined ($N = 14,973$) ending at each hour of the day over the the percentage of bids placed by hour ($N = 44,735$). Multiple bids by the same bidder on the same auction are excluded, keeping only a bidder's last bid. Vertical bars show standard error computed with the delta method.

Figure 4 Experience Increases Peak Listing But Not Peak Bidding



Notes. Lines plot the percentage of all auctions set to end during the 5 P.M.–8 P.M. period, and bids placed during such hours, by quintile of seller and bidder experience, respectively, proxied by feedback score.

visits to Amazon.com took place between 5:00 P.M. and 8:59 P.M., a figure that is quite similar to the 25.0% of eBay bids being placed at such hours. Moreover, the correlation between hourly visits to Amazon.com and hourly bids on eBay, computed with 24 observations—one for each hour of the day—is a striking $r = 0.98$.

Another approach is to consider bidders' experience. We might expect that bidders with more experience become more strategic. Simonsohn and Ariely (2008), for instance, find that experienced bidders learn not to herd behind nondiagnostic bids. If the timing of bids was a strategic decision, then it would be expected to be influenced by experience. Figure 4 depicts the share of bids placed between 5:00 P.M. and 8:59 P.M. as a function of bidder experience (as proxied by their bidder rating). The flat line for bidders shows that experience is not associated with the tendency to bid during peak bidding hours (the impact of experience on sellers is discussed later).

Another indication that bidders are not choosing their bidding time strategically is that, as we saw earlier, late bidding does not fluctuate much through the day (see Figure 1). If bidders were actively responding to supply changes through the day, they would be expected to vary the likelihood of bidding on auctions that are ending soon as a function of how saturated the time of day at which they are visiting eBay is, but they do not.

Finally, none of the advice books, discussed in detail later, nor any of the online bulletin boards I informally visited to address this question, make explicit recommendations about the time of day at which bids should be placed.

2.4.2. Supply's Peak. Because auctions end by default at the same time of day as when they are

listed, it is possible for sellers to “choose” ending times without thinking about it. It is hence conceivable that the pattern of excessive entry is the result of mindlessness rather than of competition neglect per se. To address this issue empirically, I assessed whether sellers inferred to be making ending-time decisions intentionally/strategically are more likely to end their auctions during the peak.

Intentionality, unfortunately, is of course unobservable, but I employ the following four alternative proxies for it: (i) paying a scheduling fee to opt out of the default ending time, (ii) choosing a rounded ending time (e.g., 10.00 A.M. rather than 9:59 or 10:01), (iii) consistently choosing similar ending times for different auctions, and (iv) seller experience. As we shall see, all four proxies lead to results consistent with the disproportionate entry pattern being driven by a conscious yet mistaken logic rather than by random carelessness.

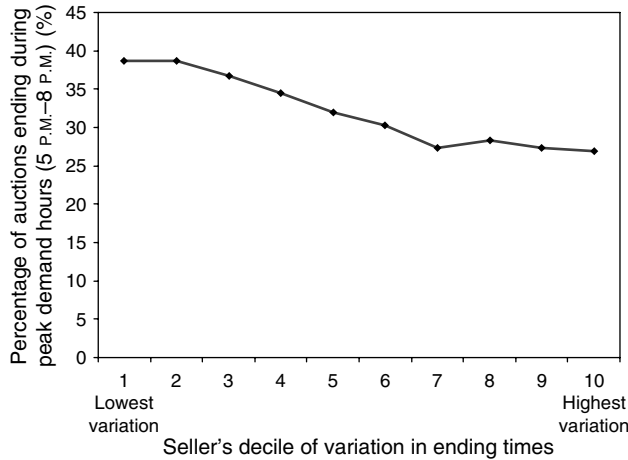
(i) *Scheduling fee.* Sellers paying this fee must explicitly set an ending time (they must type it into a textbox) so they are less likely (if at all) to list an auction without thinking about its ending time. Consistent with sellers *choosing* to disproportionately enter the peak, a higher share of auctions listed with a scheduling fee end during the peak (48%) than auctions listed without it (36%). Though the difference is quite marked, very few auctions were listed using this scheduling fee (around 1.6%), perhaps because sellers can determine the ending time of their auction *for free* by listing their item at the desired time, or by using software that will automatically list for them at a predetermined time.

(ii) *Rounded ending times.* Considering that people actively choosing a time of day are likely to choose rounded times, roundedness may act as a proxy for sellers having actively chosen an ending time.

I tested the face validity of this assumption by assessing how prevalent rounded times were among auctions listed using the scheduling fee just discussed. A striking 44.4% of scheduled auctions ended in xx:00 or xx:30, compared to just 4.1% of those listed without the scheduling fee. In the single- and multiple-DVD samples, 5.2% have a *rounded ending time*, and 46.8% of these end during the peak, a noticeably higher share than the 37.1% of nonrounded ones. Excluding auction listed with the scheduling fee, these figures are 41.7% and 36.8%, respectively.

(iii) *Consistency.* Sellers who systematically choose the same ending time for their auctions are more likely to be doing so intentionally. Unlike the previous two proxies, this one can be applied to most sellers in the sample (only sellers with few auctions are excluded), but it is a noisier proxy because sellers may intentionally spread out their auctions or they may cluster them due to external constraints.

Figure 5 Sellers Consistently Ending Auctions at the Same Time Are More Likely to End Them During the Peak



Notes. The figure plots the percentage of auctions ending during the peak (in one half of the month), listed by sellers within each decile of variation in ending times (during the other half).

To quantify *consistency* of ending time, I used a seller's average deviation of ending time across auctions (taking into account that time is reset daily, that is, that between 11:59 P.M. and 12:01 A.M. there are just 2 minutes rather than 23 hours and 58 minutes). I use variance in one half of the month to predict ending-time decisions in the other half with the full data set of DVD auctions. Sellers with less than 5 auctions in one half of the month were excluded from this analysis (the results do not vary if I exclude instead sellers with less than 3 auctions in one half of the month, or with less than 10). Figure 5 plots sellers' average percentage of auctions ending during the peak demand period of 5:00 P.M. to 8:59 P.M. by sellers' decile of standard deviation in ending times. It shows 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 variation set around 39% of the auctions during the period of peak demand, whereas those in the highest decile do so for just 27% of them.

(iv) *Experience.* The fourth variable used to proxy for intentionality is *experience*. As was argued with bidders, one would expect that experience increases the prevalence of strategic behavior among sellers. Figure 4 plots share of auctions listed during the peak as a function of seller *experience*; it shows a marked increase in sellers' tendency to end auctions during peak bidding hours as a function of experience. This result is again consistent with the notion that the sellers responsible for excessive entry are those that are most likely to be strategically choosing the end time of their auction.

2.5. Convenience as an Alternative Explanation

In this section, I consider the possibility that the disproportionate share of auctions ending during the peak is caused by the greater "convenience" associated with *listing* items at such hours. Considering that by default an auction's ending time coincides with the time of day at which it is listed, if listing during peak hours is less costly, then it may be optimal for a disproportionate share of sellers to do so, even if—as we shall see in the next section—it leads to lower probability of sale and prices.

The assumption on which such a story relies is reasonable; listing costs may very well vary through the day as a function, for example, of the opportunity cost of time. Note, however, that to explain a more pronounced peak for auctions, the listing cost explanation requires that for sellers the cost differences through the day are steeper than for bidders.

A listing cost-based explanation leads to several testable predictions. First, sellers who would be expected to face flatter listing costs through the day, such as stores, large sellers, and sellers listing on weekends, should exhibit a less pronounced peak. This, however, is not the case because these subsets of sellers end 38%, 45%, and 34%, respectively, of their auctions during the peak (compared to, recall, 37.6% of *all* auctions and 25% of bids).

Similarly, because the (differential) cost of listing an item during peak demand hours is probably not dependent on the value of the item being listed, more expensive items should be more likely to be listed off peak (because the benefits of doing so are greater but the costs constant). More expensive items do show some attenuation in peak entry, but it is quite slight. For example, 32% of items starting at \$30 or above end in the peak, and 33% of those starting above \$60 do.

Finally, sellers who paid the scheduling fee face a constant cost of ending an auction at any time of the day, and should therefore exhibit the least peak listing of all, but as was reported above, they show a *more* pronounced peak (48% of such auctions end in the peak).

An alternative explanation closely related to the listing cost explanation is that sellers may want to be around when an auction ends, and being around during peak demand hours may be more convenient. This explanation makes the same predictions as the listing cost explanation, with the exception that scheduled auctions would not need to show a less pronounced peak. It makes the additional prediction that auctions *ending* on a weekend would be less likely to end during the peak, but 36% of them do.

3. Excessive Entry's Impact on Profits

This section presents results estimating the consequences for probability of sale and selling prices of

listing an item during periods of peak versus off-peak demand. I present results for three alternative measures of peak listing. The first is a set of 23 hourly dummies. Their main advantage is that they create an intuitive and easy to display result. Indeed, I plot the point estimates for these dummies in Figures 6 and 7, creating an easy-to-visualize daily pattern in probabilities of sale and expected final prices. Their main disadvantage, on the other hand, is that it is difficult to compare the impact on so many different point estimates of controlling (versus not) for observable heterogeneity. For this reason I also present regression tables that use a single key independent variable as a predictor. I consider two: ratio of the percentage of daily auctions ending over the percentage of daily bids being placed during an auction's last 180 minutes (A/B ratio), and a *peak* dummy that equals 1 if an auction ends during one of the four most popular hours of the day and 0 otherwise.

In all regressions, auctions are the unit of observation. For the probability of sale regressions, I estimate probit regressions. For the price estimates, I run both tobit and ordinary least squares (OLS) regressions. The OLS regressions include only sold items, whereas the tobit regressions include all items and treat unsold ones as censored at the starting price.

Figures 6 and 7 plot the results of the regressions that employ hourly dummies as predictors. Figure 6 has the results for the single-DVD sample and Figure 7 for the multiple-DVD sample. In both figures, the bold discontinued lines show the A/B ratio computed on the respective sample.⁶ The solid black lines depict marginal effects for the hourly dummies from the probit regressions, whereas the solid gray lines depict the marginal effects from the tobit price regressions. The tobit marginal effects were computed for final prices conditional on them being above the auction's starting price/censoring point (i.e., $E(y | XB, y > y_{\min})$). All marginal effects are computed at sample means.

In Figure 6, both solid lines show a marked drop that coincides with the peak of the dashed line: At times of day when sellers disproportionately enter the single-DVD market, both prices and probability of sale show a marked decrease. Prices around 8 P.M., for instance, are \$0.38 lower than around noon, and probability of sale is around 14 percentage points lower. The sample averages for these are \$10.16 and 71%, respectively.

In Figure 7 the overall pattern is quite similar; here too both probability of sale and prices drop at the

times of day when sellers are disproportionately ending their auctions. Prices around 8 P.M., for example, are \$3.40 lower than around noon, and probability of sale is about 5 percentage points lower; the respective sample means are \$55.9 and 90%.⁷

To present the impact of the other covariates on the dependent variables and to assess the impact of the inclusion of such covariates on the point estimates for the key independent variable, I now turn to the regressions that employ a single predictor rather than the 23 hourly dummies.

When using the A/B ratio as a predictor to identify the impact of ending time on auction outcomes that operates only through *predictable* variation in it (rather than of contemporaneous shocks that sellers could not anticipate), instead of employing as a regressor the A/B ratio of the time when auctions actually end, I used the *average* ratio for that same time for all *other* days in the sample. For example, the outcome of an auction ending on Tuesday, October 8, at 8.45 P.M. was predicted with the average A/B ratio between 5:46 P.M. and 8:45 P.M. for all other working days in October. Because of some differences in the timing of auctions and bids between samples, and between working and nonworking days, the average A/B ratio was computed separately for each of these four subsets of auctions.⁸

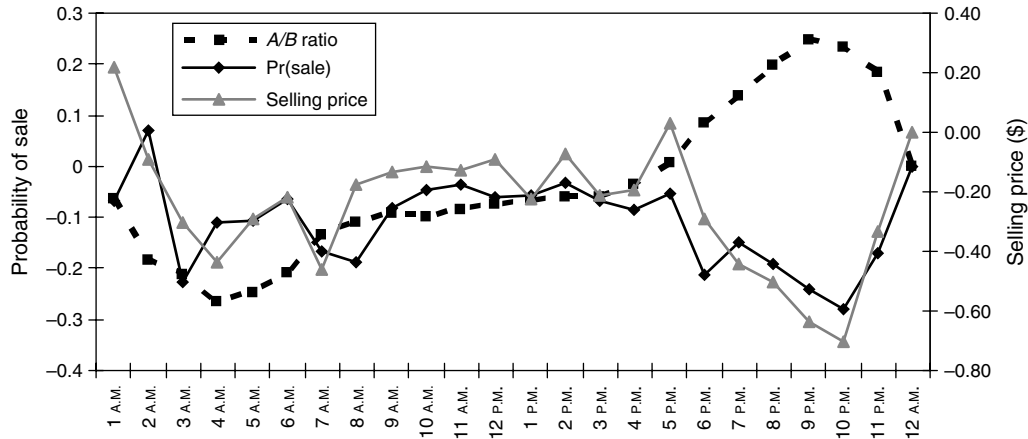
I estimated probit regressions with auctions as the unit of observation. The dependent variable equals 1 if an item sold and 0 otherwise, and the key predictor is the A/B ratio. The regressions also include the various controls for movie, auction design, and seller observable differences mentioned above.

⁷ Between 12 A.M. and 1 A.M. there are just 49 multiple-DVD auctions; the point estimates for the corresponding hourly dummies in the price regression are, hence, very noisy and were not included in Figure 7 to improve readability. The missing values are $\Delta Y/\Delta X_{12 \text{ A.M.}} = -\6.56 , $\Delta Y/\Delta X_{1 \text{ A.M.}} = -\8.27 . Also, to provide a reliable comparison between 8 P.M. and noon, I compare the *average* marginal effect between 7 P.M. and 9 P.M. with the average between 11 A.M. and 1 P.M., rather than use a single estimate at 8 P.M. and 12 P.M., respectively.

⁸ In line with the discussion prompted by a referee of generated regressors in Footnote 5, because the A/B ratio is an average, its sampling error should be considered when computing the standard errors of the regressions described above, but it is not. To assess the importance of this problem I, compared the standard errors obtained with a linear probability model where the ratio is entered as a predictor (ignoring its sampling error) with those obtained with a two-stage least squares regression where in the first stage the A/B ratio is estimated based on hourly dummies, and the second stage uses the predicted A/B ratio, taking into account its sampling error, to predict probability of sale. The resulting standard errors are about 5% *lower* in the two-stage regression, suggesting the impact of the generated regressor's sampling error is trivial. For simplicity of exposition, I report the results from the one-stage estimators. Note that the *peak* dummy (used columns (4) and (8) of Table 2) is not a generated regressor.

⁶ To keep the graph with just two Y -axes, the A/B ratio was rescaled by adding a constant to it. Neither axis in the graph represents the actual values of the A/B ratio.

Figure 6 Time of Day, Probability of Sale, and Prices (Single-DVD Sample)



Notes. For Pr(sale) and selling price, the lines plot the point estimates for hourly dummies in probit and tobit regressions, respectively, controlling for all observables listed in Tables 2 and 3 ($N = 11,796$). The A/B ratio has been rescaled to fit into the existing Y -index; it lacks an absolute meaning in this figure.

Table 2 displays the results, expressed as marginal effects (i.e., as changes in predicted probability of sale as the independent variable is increased in 1 unit). Columns (1)–(4) show the results for the single-DVD sample and columns (5)–(8) for the multiple-DVD sample. The bottom row in the table displays the estimated impact on probability of sale of ending the auction during a peak versus off-peak hour, to make the results obtained through the multiple specifications easy to compare.

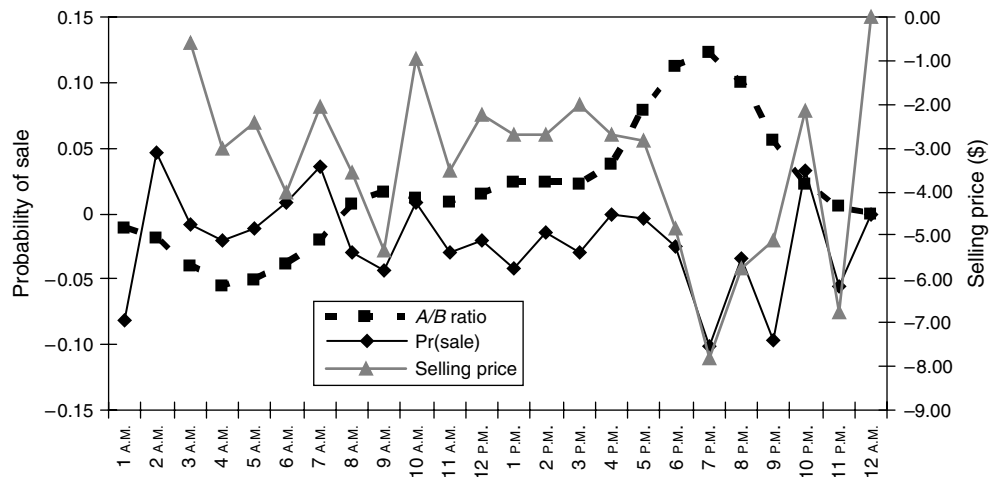
The point estimate for the A/B ratio is negative in all columns, and it is significant in all of them as well, with the exception of column (5) (multiple-DVD sample without covariates); consistent with Figures 6 and 7 this indicates that at times of day when there are relatively more auctions per bid, a systematically smaller share of auctions sell. The effect of

the A/B ratio does noticeably attenuate as controls are added to the regression in the single-DVD sample ($\beta_{(1)} = -0.355$, $\beta_{(3)} = -0.289$), but it is augmented in the multiple-DVD sample ($\beta_{(4)} = -0.125$, $\beta_{(6)} = -0.243$), alleviating concerns that the results might be driven by omitted variable bias.

Focusing on the bottom row, which contains the marginal effect of ending an auction in the peak versus off peak, we see that ending an auction in the peak drops probability of sale by about 6%–7% in the single-DVD sample, and by about 4% in the multiple-DVD sample. Note that the marginal effects estimated with the peak dummy (columns (4) and (8)) are very similar to those obtained with the A/B ratio.

The marginal effects for all other variables are as would be expected; auctions with lower starting and reserve prices, and lower shipping costs, those

Figure 7 Time of Day, Probability of Sale, and Prices (Multiple-DVD Sample)



Notes. For probability of sale (Pr(sale)) and selling price, the lines plot the point estimates for hourly dummies in probit and tobit regressions, respectively, controlling for all observables listed in Tables 2 and 3 ($N = 3,117$). The A/B ratio has been rescaled to fit into the existing Y -index; it lacks an absolute meaning in this figure.

Table 2 Impact of Market Saturation When Auction Ends on Probability of Sale (Probit, Marginal Effects)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|-----------------------------|---------------------------|-----------------------------|-----------------------------|---|----------------------------|-----------------------------|-----------------------------|
| Sample: | Single DVD (movies) | | | | Multiple DVDs (TV seasons and compilations) | | | |
| <i>A/B</i> ratio (auction's last 180 min.) | -0.355*** (0.034) | -0.30*** (0.03) | -0.289*** (0.031) | | -0.125 (0.102) | -0.222** (0.090) | -0.243*** (0.091) | |
| Peak (equals 1 if auction ends during one of the four most popular hours) | | | | -0.077*** (0.009) | | | | -0.040*** (0.013) |
| Starting price (minimum \$ amount of first bid) | | -0.067*** (0.002) | -0.067*** (0.002) | -0.066*** (0.002) | | -0.0026*** (0.0003) | -0.0026*** (0.0003) | -0.0025*** (0.0003) |
| Reservation price (secret minimum price at which seller would sell) | | -0.045*** (0.01) | -0.041*** (0.011) | -0.041*** (0.011) | | -0.0021*** (0.0003) | -0.0021*** (0.0003) | -0.0020*** (0.0003) |
| Shipping charges (set by seller) | | -0.034*** (0.004) | -0.028*** (0.004) | -0.026*** (0.004) | | -0.0083*** (0.0021) | -0.0079*** (0.0021) | -0.0081*** (0.0020) |
| Duration of auction (days; auctions last 3, 5, 7, or 10 days) | | 0.0076*** (0.002) | 0.007*** (0.002) | 0.008*** (0.002) | | 0.0031 (0.0020) | 0.0033 (0.0021) | 0.0030 (0.0020) |
| Weekend dummy (equals 1 if auction ends on a weekend) | | 0.019** (0.009) | 0.019** (0.009) | 0.005 (0.009) | | 0.0246*** (0.0092) | 0.0250*** (0.0092) | 0.0187** (0.0089) |
| Log(<i>seller rating</i> + 1) (seller rating: sum of +1, 0-1 feedback scores) | | | 0.027*** (0.003) | 0.028*** (0.003) | | | -0.0007 (0.0022) | -0.0004 (0.0023) |
| Store dummy (equals 1 if seller has contract with eBay) | | | -0.092*** (0.017) | -0.088*** (0.017) | | | -0.0453** (0.0184) | -0.0465** (0.0185) |
| DVD title fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| New dummy * DVD title | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Implied marginal effect on Pr(sale) of ending on peak (vs. off peak) (%) | -6.9% | -5.9% | -5.5% | -7.7% | -2.1% | -3.8% | -4.1% | -4.0% |
| Number of observations | 11,695 | 11,695 | 11,695 | 11,695 | 2,937 | 2,937 | 2,937 | 2,937 |

Notes. The dependent variable equals 1 if the auction sold, 0 if it did not. Entries in the table correspond to *marginal effects* estimated at sample means (i.e., impact on the dependent variable of increasing the independent variable in one unit) obtained employing a probit regression. Robust standard errors are reported in parentheses below marginal effects. *A/B* ratio is the ratio of the percentage of daily auctions ending during the auction's last 180 minutes to the percentage of daily bids over the same time period. Key point estimates, of variables capturing peak listing, are shown in bold.

*, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

lasting more days, and those listed by more experienced sellers are all more likely to sell. The sole surprising result is that of the *store* dummy, which is negative, indicating that sellers who have a contractual agreement with eBay are less likely to sell their auctions. The effect of *store* controlling for reputation ($\log(\text{seller rating})$), however, is hard to interpret, as one might expect that being a store improves a seller's performance through reputation. If the regression is estimated without controlling for reputation, the marginal effect of *store* is positive and significant.

To estimate the impact of ending time on selling price, I estimated regressions with auctions as the unit of observation. The dependent variable equals the selling price for sold auctions and, in the tobit specifications, the starting-price for nonsold/"censored" auctions.

The results of these regressions are displayed in Table 3. For the tobit specifications, I report marginal effects on price conditional on sale ($E(y | XB, y > y_{\min})$). Robust standard errors are reported below point estimates. Columns (1)–(5) show the results for the single-DVD sample, and columns (6)–(10) for the multiple-DVD sample. The bottom row in the table

displays the estimated impact on selling prices caused by ending the auction during a peak versus off-peak hour to facilitate comparison across columns and to provide an intuitive sense of the practical significance of the results.

The point estimate for the *A/B* ratio (and for the *peak* dummy) is negative and significant at the 1% level across all columns. The effect of the *A/B* ratio is estimated as larger for both samples when observable heterogeneity is versus is not controlled for, suggesting these results are not due to omitted variable bias.⁹

The marginal effects for all other predictors in Table 3 are as would be expected; auctions with higher starting prices and reserve prices, those with lower shipping costs and lasting more days, and

⁹ As was discussed in Footnote 5, the *A/B* ratio is a generated regressor, and hence the true standard errors may be larger than those estimated in Table 3. As was done with the Pr(sale) regression, I assessed the potential importance of this problem with a two-stage regression where in the first stage the ratio is regressed on hourly dummies. Here the standard errors are about 5% higher in the two-stage estimation; the change does not alter the significance of the point estimates.

Table 3 Impact of Market Saturation When Auction Ends on Selling Prices

| Sample: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|--|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------------|------------------------------|------------------------------|------------------------------|-----------------------------|
| | Single DVD (movies) | | | | | Multiple DVDs | | | | |
| Regression type: | Tobit | Tobit | Tobit | OLS | Tobit | Tobit | Tobit | Tobit | OLS | Tobit |
| <i>A/B</i> ratio (auction's last 180 min.) | -0.828*** (0.143) | -1.066*** (0.116) | -1.017*** (0.115) | -0.683*** (0.179) | | -13.903*** (4.368) | -17.270*** (4.913) | -18.971*** (4.909) | -16.003*** (5.240) | |
| Peak (equals 1 if auction ends during one of the four most popular hours) | | | | | -0.273*** (0.030) | | | | | -2.924*** (0.666) |
| Starting price (minimum \$ amount of first bid) | | 0.033*** (0.006) | 0.040*** (0.006) | 0.129*** (0.010) | 0.041*** (0.006) | | 0.125*** (0.002) | 0.120*** (0.002) | 0.071*** (0.012) | 0.124*** (0.002) |
| Reservation price (secret minimum price at which seller would sell) | | 0.077 (0.065) | 0.107* (0.063) | 0.415*** (0.139) | 0.106* (0.063) | | 0.077*** (0.017) | 0.084*** (0.016) | 0.077*** (0.016) | 0.087*** (0.017) |
| Shipping charges (set by seller) | | -0.272*** (0.021) | -0.246*** (0.021) | -0.355*** (0.036) | -0.243*** (0.021) | | -0.706*** (0.128) | -0.752*** (0.128) | -0.606*** (0.112) | -0.776*** (0.128) |
| Duration of auction (days; auctions last 3, 5, 7, or 10 days) | | 0.058*** (0.001) | 0.057*** (0.001) | 0.068*** (0.011) | 0.058*** (0.001) | | 0.612*** (0.117) | 0.609*** (0.116) | 0.203*** (0.074) | 0.599*** (0.115) |
| Weekend dummy (equals 1 if auction ends on a weekend) | | -0.040 (0.031) | -0.043 (0.030) | -0.163*** (0.047) | -0.089*** (0.030) | | 1.084** (0.479) | 1.041** (0.476) | -0.308 (0.373) | 0.449 (0.416) |
| Log(<i>seller rating</i> + 1) (seller rating: sum of +1, 0-1 feedback scores) | | | 0.198*** (0.011) | 0.267*** (0.015) | 0.201*** (0.011) | | | 0.691*** (0.112) | 70.653*** (0.095) | 0.725*** (0.114) |
| Store dummy (equals 1 if seller has contract with eBay) | | | -0.144*** (0.048) | -0.024 (0.074) | -0.134*** (0.048) | | | -0.919 (0.636) | -0.246 (0.511) | 0.642*** (-1.600) |
| DVD title fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| New dummy * DVD title | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Implied marginal effect on price of ending on peak (vs. off peak) (\$) | -\$0.16 | -\$0.21 | -\$0.20 | -\$0.13 | -\$0.27 | -\$2.39 | -\$2.97 | -\$3.26 | -\$2.75 | -\$2.92 |
| Number of observations | 11,796 | 11,796 | 11,796 | 8,355 | 11,796 | 3,177 | 3,177 | 3,177 | 2,849 | 3,177 |

Notes. Dependent variable: *Selling price* (censored at starting price for tobit regressions). Entries in columns (1)–(3) and (5)–(7) correspond to marginal effects ($E[\text{price} | XB, \text{price} > \text{starting price}]$) from tobit regressions where final prices of unsold auctions are considered censored at the auction's starting price. Entries in columns (4) and (8) are point estimates from OLS regressions that exclude unsold auctions. Robust standard errors are reported in parentheses below parameter estimates. *A/B* ratio is the ratio of percentage of daily auctions ending during the auction's last 180 minutes to the percentage of daily bids (counting only one bid per bidder per auction) over the same time period. Key point estimates, of variables capturing peak listing, are shown in bold.

*, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

those listed by more experienced sellers are all more likely to sell. The sole surprising result is again the *store* dummy, which is negative, but also here it becomes positive if the regression is estimated without controlling for seller reputation.

4. Expert Advice on eBay Books

The growing popularity of eBay has led to a proliferation of publications dedicated to help both buyers and sellers who participate on it. The recommendations printed in these books can safely be assumed to consist of an upper bound of the typical eBay seller's sophistication, as "experts" presumably write them. 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.

A research assistant (blind to the hypothesis of this paper) collected and summarized ending-time recommendations from all (26) eBay books available at two

local bookstores. Books were then categorized as giving no recommendation, or as giving one based on aggregate or residual demand.

Eight books did not mention ending time, or consider either demand or supply in their recommendation. Fourteen books made a recommendation based on aggregate demand alone, and hence fell prey to competition neglect. For example, the book "*eBay Strategies*" (Wingo 2004) has the following recommendation: "Timing your auctions to end during peak times will significantly improve traffic to your auctions, resulting in more bids" (they then recommend 5 P.M.–9 P.M. Pacific time).

Only two books took into account competition when making ending-time recommendations. For example, the aptly titled *eBay Myth-Buster* (Busch 2004) states, "If selling a fairly common item, high-traffic nights might be the absolute worst time to close (too much competition)."¹⁰

¹⁰ Two books gave ambiguous advice that could not easily be classified.

The content of the eBay books, in sum, supports the interpretation given to the excessive entry pattern: all advice is a function (only) of demand considerations and primarily only of aggregate demand. This means that, on one hand, eBay sellers literally engage in competition neglect rather than simply behave as if they did, and on the other, that none of the alternative explanations I consider (or any I do not for that matter) are even mentioned by eBay experts (e.g., no book suggests listing in the evenings because it is more convenient to do so, or that bidders choose bidding times based on when the most auctions are ending).

5. Conclusions

Based on the experimental and survey-based literatures documenting competition neglect, i.e., players' tendency underestimate the impact of their competitors' actions, I hypothesized that firms would tend to oversupply high-demand markets. Exploiting the fact that bidders bid at the last minute on online auctions, creating sequentially and at least partially independent markets, I tested this hypothesis by studying the ending-time decisions of eBay sellers. As predicted, a disproportionate fraction of them end their auctions during peak hours, leading to *lower* probability of sale and final prices during such hours. This excessive entry appears 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 commodities has two notable advantages. The first is that, unlike most other settings, markets here differ *only* in their demand levels, making comparisons of outcomes across markets much easier to interpret; there are no potential confounds of entry costs, required expertise, uncertainty, and so on. 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.

The chosen setting, however, is of course not free of disadvantages. In particular, although determining the time of day to end an auction is in theory analogous to a market entry decision, there are noticeable differences between them in practice. Most notably, the decisions studied here are repetitive and for relatively small stakes, whereas market entry decisions are typically infrequent and for very large stakes. Similarly, market entry decisions are made by

a few "experts" or entrepreneurs, whereas ending-time decisions are made by individual sellers (though many of them are firms).

There are two points worth considering with regard to these limitations. The first is that agents making repetitive decisions would be expected to act *more* rationally than those making one-off decisions, by virtue of having had more opportunities to learn from feedback. The second is that in the data used here, larger sellers were more rather than less likely to exhibit competition neglect.

Another concern with the present study is the possibility that DVDs are an odd product for eBay. In particular, if it is typically the case that goods sold on eBay do not have close substitutes, then ignoring competition may be a fine strategy for most sellers most of the time. On eBay, however, goods with substitutes are the norm rather than the exception. In early August 2009, for instance, there were over 1.6 million auctions for computer and networking products, over 1.3 million for DVDs, and over 4 million for books (excluding antique and collectible books); on the same day there were just over 200,000 auctions for antiques and just over 260,000 for entertainment memorabilia.¹¹

In addition, sellers offering large numbers of DVDs probably specialize in the sale of such products (few sellers would be expected to sell both rare dolls, say, and best-seller DVDs), and hence peak listing is unlikely to usually be an optimal strategy *for them*.

In terms of generalizability of the findings, intuitively, excessive entry is more likely to occur in situations where sellers do not receive feedback about the profitability of supplying off peak. This is likely to occur, for example, in settings where independent small sellers make and observe one or just a few entry decisions, as is the case with entrepreneurs who own small businesses (e.g., independent restaurants) or with people's decisions of investment in human capital (e.g., deciding what major to study or where to look for work). It is less likely to occur in settings where large firms make repetitive decisions, such as food chains deciding on new locations for their restaurants.

Excess entry into peak demand markets is also likely to occur in industries where a high-demand market is so focal that even large sellers will not have experimented with off-peak demand, as seems to be the case with the movie industry's reluctance to launch blockbuster films on nonpeak movie-going weekends (Einav 2007).

In closing, this paper demonstrates the importance for marketing research that relies on field data to

¹¹ Source. eBay Categories. Retrieved August 6, 2009, <http://listings.ebay.com>

assess rather than assume the rationality of agents being studied.

Acknowledgments

The author thanks Gérard Cachon, Stefano DellaVigna, Uri Gneezy, Ulrike Malmendier, Devin Pope, Todd Sinai, Justin Sydnor, Matthew White, and attendees at the Psychology and Economics seminar at Berkeley, the Behavioral Economics seminar at Cornell, and the Applied Economics seminar at Wharton for valuable feedback on earlier versions of this paper. He also thanks Dan Ariely for providing some of the data used in this paper.

Appendix A. How Movie Titles Were Inferred from Item Descriptions

As was mentioned in the data description, eBay does not utilize unique product identifiers for their listings, so bidders and researchers must rely on sellers' descriptions of their items to identify what's being auctioned. Bidders can easily do this because they see but a handful of auctions, which, furthermore, they come across only after querying relevant keywords themselves.

As a researcher interested in identifying several thousand items, in contrast, I had to develop an at least partially automatized process to do this. To this end I selected a set of DVD titles against which the seller descriptions were to be automatically compared (see Appendix B for details on the selection of such titles).

For each movie title I chose a few keywords to search in the descriptions of each of the over 500,000 auctions in the DVD category. For example, for the movie *A Walk to Remember*, items whose descriptions contained the keywords "walk" and "remember" were initially classified as such movie.

Because different movies often have similar names, this initial process lead to a nontrivial share of false positives that included completely different movies with similar names, closely related films (e.g., sequels and remakes), and different DVD versions of the same original movie.

To systematically identify these false positives, I tabulated, for each movie, all words used in the descriptions of all items. The resulting list was then inspected "by hand" for suspicious words that may indicate a false positive.

For example, among auctions categorized as *Gladiator* (the Oscar winning film) the word "Eroticvs" appeared five times. By reading the full description of the corresponding listings I discovered the existence of the film *Gladiator Eroticvs*, a different movie altogether. The word "Jurassic" also appeared on a few other descriptions of auctions identified as "Gladiator." Upon examining their full descriptions, it was determined that these auctions offered a bundle that included two films: *Gladiator* and *Jurassic Park*. Finally, the high frequency of the word "Signature" pointed to the fact that there were—at the time—two versions of *Gladiator*, a standard one (containing two DVDs) and a "signature series" one (containing three). For this process I supplemented my personal movie knowledge with the websites Amazon.com, IMDB.com, and DVDcompare.net.¹²

¹² DVDcompare.net provides detailed information on different DVD versions of the same movie.

This process is obviously very time intensive. Because the time it takes to identify false positives is relatively fixed per movie *title* rather than per auction, I constructed the subsamples based on popular titles; that way, a maximum number of observations was obtained with a given amount of time devoted to data cleaning. Not a single classification or exclusion was made based on the impact of excluding that/those observation(s) from the sample on the regression results.

Appendix B. Selection of Movie Titles

The single-DVD list of movies corresponds to movies appearing on a weekly top-20 list on the Internet Movie Database archive (<http://www.imdb.com>) at least once during the two months immediately before the sample's month, or listed as the top-20 best sellers for the previous year.

I am not aware of any best-seller list for multiple-DVD sets. To identify common titles, I tabulated the word frequency of auctions selling for more than \$30. I eliminated all words used less than 100 times, and also eliminated those that were generic descriptors rather than movie title identifiers (e.g., "DVD," "NEW," "shipping," etc). The list of words that remained was then used to uncover titles of multiple-DVD sets often sold on eBay.

References

- Bajari, P., A. Hortacsu. 2004. Economic insights from internet auctions. *J. Econom. Literature* 42(2) 457–486.
- Busch, D. D. 2004. *The eBay Myth-Buster: Turn 199 Misconceptions Into Money! (for Dummies Series)*, 1st ed. Wiley, Hoboken, NJ.
- Camerer, C. F., D. Lovo. 1999. Overconfidence and excess entry: An experimental approach. *Amer. Econom. Rev.* 89(1) 306–318.
- Che, H., K. Sudhir, P. B. Seetharaman. 2007. Bounded rationality in pricing under state-dependent demand: Do firms look ahead, and if so, how far? *J. Marketing Res.* 44(3) 434–449.
- DellaVigna, S. 2009. Psychology and economics: Evidence from the field. *J. Econom. Literature* 47(2) 315–372.
- DellaVigna, S., J. Pollet. 2007. Demographics and industry returns. *Amer. Econom. Rev.* 97(5) 1167–1702.
- DellaVigna, S., J. Pollet. 2009. Investor inattention and Friday earnings announcements. *J. Finance* 64(2) 709–749.
- Einav, L. 2007. Seasonality in the U.S. motion picture industry. *RAND J. Econom.* 38(1) 127–145.
- Eisenstein, T., D. Strömberg. 2007. News droughts, news floods, and U.S. disaster relief. *Quart. J. Econom.* 122(2) 693–728.
- Goldfarb, A., M. Xiao. 2010. Who thinks about the competition? Managerial ability and strategic entry in US local telephone markets. Working paper, University of Toronto, Toronto, ON.
- Goldfarb, A., B. Yang. 2009. Are all managers created equal? *J. Marketing Res.* 46(5) 612–622.
- Grisprud, G., K. Gronhaug. 1985. Structure and strategy in grocery retailing: A sociometric approach. *J. Indust. Econom.* 33(3) 339–347.
- Hirshleifer, D. A., S. S. Lim, S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *J. Finance* 64(5) 2289–2325.
- Hossain, T., J. Morgan. 2006. Plus shipping and handling: Revenue (non)equivalence in field experiments on eBay. *Advances Econom. Anal. Policy* 6(2) Article 3, <http://www.bepress.com/bejeap/advances/vol6/iss2/art3>.
- Hsee, C. K., J. P. Dube, Y. Zhang. 2008. The prominence effect in Shanghai apartment prices. *J. Marketing Res.* 45(2) 133–144.

- Lee, H., U. Malmendier. 2010. The bidder's curse. *Amer. Econom. Rev.* Forthcoming.
- Milkman, K. L., T. Rogers, M. H. Bazerman. 2009. Highbrow films gather dust: Time-inconsistent preferences and online DVD rentals. *Management Sci.* 55(6) 1047–1059.
- Moore, D. A., B. M. Cain. 2007. Overconfidence and underconfidence: When and why people underestimate (and overestimate) the competition. *Organ. Behav. Human Decision Processes* 103(2) 197–213.
- Moore, D. A., J. M. Oesch, C. Zietsma. 2007. What competition? Myopic self-focus in market-entry decisions. *Organ. Sci.* 18(3) 440–454.
- Ockenfels, A., D. Reiley, A. Sadrieh. 2006. Online auctions. NBER Working Paper 12785, National Bureau of Economic Research, Cambridge, MA.
- Porac, J. F., H. Thomas, C. Baden-Fuller. 1989. Competitive groups as cognitive communities: The case of Scottish knitwear manufacturers. *J. Management Stud.* 26(4) 397–416.
- Radzevick, J. R., D. A. Moore. 2008. Myopic biases in competitions. *Organ. Behav. Human Decision Processes* 107(2) 206–218.
- Simonsohn, U. 2006. New Yorkers commute more everywhere: Contrast effects in the field. *Rev. Econom. Statistics* 88(1) 1–9.
- Simonsohn, U. 2010. Lessons from an oops at Consumer Reports®: Consumers follow experts; ignore invalid information. *J. Marketing Res.* Forthcoming.
- Simonsohn, U., D. Ariely. 2008. When rational sellers face non-rational buyers: Evidence from herding in online auctions. *Management Sci.* 54(9) 1624–1637.
- Simonsohn, U., G. Loewenstein. 2006. Mistake #37: The impact of previously observed prices on housing demand. *Econom. J.* 116(1) 175–199.
- Wingo, S. 2004. *eBay Strategies: 10 Proven Methods to Maximize Your eBay Business*. Prentice Hall, Upper Saddle River, NJ.