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ABSTRACT

Auctions are often not independent from each other, and the movement of bidders across different auctions is one of the key linkages. We propose different measures of bidder movements (which we call bidder migration in this paper) and how such migration affects the price outcome of later auctions. Moreover, we identify two potentially confounding effects: the learning effect where bidders learn to become more sophisticated bidders, hence driving down the price of later auctions; and the desperation effect where bidders, in a hope to obtain the product that they previous couldn't win, tend to increase the prices. We empirically investigated these effects using bidding history data from eBay and Generalized Linear Model specifications. We further discussed potential applications of bidder migration for online auction platforms, such as bidder segmentation, dynamic promotions, and shill bidder detection. These bidder migration measures can be provided to internet auction sellers as a value-added service,

Keywords

Online auctions, bidder migration, bidder learning, competition among auctions

INTRODUCTION

A fundamental question of a market mechanism is how to efficiently allocate scarce resources, and the fundamental principle of the welfare economics suggests that efficiency is achieved when these resources are allocated to those with the highest willingness to pay: competitive equilibrium is Pareto optimal. However, even when such optimal allocation can be achieved, the literature has said very little about what happens to those parties whose demand stay unfulfilled and, consequently, "migrate" to other auctions (Bapna 2004). When these migrating buyers – or bidders in an auction setting – re-appear in later transactions, will they behave differently from other buyers? Will their presence affect the outcome of the auction (e.g. price), and will it affect process through which the final prices of the auctions are reached? Our literature review finds that other than anecdotal evidence of consumer learning or bidder experimentation (Armantier 2004), we do not yet know the relationship between bidder migration and its effect on the market outcome, especially from the perspective of sellers or auctioneers. This is also part of an emerging literature on the relationship among auctions.

From the perspective of service research, a bidder's history is valuable information for market participants, especially sellers on auctions. However such information is largely missing from existing auction platforms. Our paper argues that information about bidders' history, such as measurements of bidder migration, can be easily implemented by auction platforms and then be provided to market participants as a value-added service. Such services, by increasing information transparency, could potentially lead to overall efficiency gains.

To fill this gap in literature as well as practice, we address the following specific questions in this study: What are the meaningful measures of bidder migration? How significant is the phenomenon of bidder migration? Does the migration affect the outcome of an auction and if so, how? How does the migration affect the price dynamics of auctions? And, how do bidders adapt or change their bidding strategies over time as a result of migration?

From the perspective of auction practitioners, the study of bidder migration can provide benefits at least in the following aspects. Firstly, as we shall see, measurements of bidder migration provide additional and much richer information about bidders than the feedback scores. Such measurement can also be given on a specific category level, and can be provided to sellers prior to their listing so that they would be able to better configure the auction to achieve the highest final price. Secondly, with additional information about bidders becoming available, sellers can even provide targeted promotions to potential bidders or buyers. Last but not least, auction marketplace such as eBay can provide related measurements to sellers as a value-added service.

We start by deriving several measures for bidder migration with different levels of granularity. **Bidder migration** is broadly defined in our paper as the sequential movement of bidders across auctions with different ending time. Typical bidder behavior in auctions includes observation (watching the progress of auctions) and participation, of which placing bids is the most consequential type for the sellers and the auction mechanism; therefore it is the focus of our current study. We focus on the sequential migration of bidders among different auctions offering the same product. Concentrating on a single product is a starting point for us to understand more general inter-auction relationships through bidder migrations, such as those from one product to another (substitute and complementary products).

Using TreeMap software, we empirically demonstrate the prevalence of bidder migration in our sample. Furthermore, our data analysis shows that the dominating effect of migrating bidders appear to be a downward pressure on the price of later auctions.

Bidder migration is not a new phenomenon, but the data collection would have been much more difficult in an offline setting.

CONCEPTUAL BACKGROUND AND LITERATURE REVIEW

The phenomenon of bidders migrating from one auction to another has implications beyond auctions. The process that buyers on markets are matched with sellers can also be considered a process of auction in the framework of Walrasian Tâtonnement. This process, introduced by Leon Walras and widely adopted in economics, presume an auction process to find the market clearing prices for all products that give rise to the concept of general equilibrium, where demand and supply in all markets clear at the same time. Perfect information and no transaction costs are implicitly assumed in this process.

Few studies have been conducted, particularly empirical ones, on the topic of bidder or buyer learning across transactions. The lack of data is likely to be the most important reason. In this section, we will review the current literature on consumer learning and the role of experience in marketing and economics literature, with an emphasis on those related to auctions. As will be shown, while some previous research has touched upon the topic of learning and experience, our current study is unique in several ways:

1) We use more comprehensive and detailed transaction history data than has been previously available;

2) We propose a system of increasingly sophisticated measures of bidder migration; and

3) We empirically separate two confounding effects that could occur when buyers migration from one transaction to another.

A number of theoretical researchers, especially in economics, have studied the role of experience or learning that could affect the outcome of transactions, particularly auctions. For instance, Hon-Snir, Monderer and Sela (1998) analytically modeled the role of learning in first-price auctions, where bidder types are determined before the first round. They showed that after sufficiently long time, the bidders' bids are identical, in equilibrium, to those in the one-shot games where bidder types are commonly known. This suggests that at least in the context of their analysis, theoretical predictions from auction theories can only hold after bidders learned. It highlights the importance of better understanding the process through which bidders learn from their experience, which is one of the focuses of our paper. In another analytical paper, Jeitschko (1998) studied the role of information transmission and learning in a model of sequential auctions, where bidders have independent private values. Winning bids in these auctions can be used by participants in the auction to infer opponent types, which in turn affects the "price path" of sequential auctions. Horner and Jamison (2008) also proposed an analytical model of sequential common-value auctions with asymmetrically informed bidders. These theoretical processes can be regarded as a special case of what we discuss in this paper, where the pool of bidders remains constant across auctions. In real-world auctions, however, the pool of bidders changes frequently, especially when some bidders exit the market after losing or winning in previous auctions, or when new bidders arrive.

Some authors in recent years have also empirically explored this topic using data from real auctions or experiments. Wilcox (2000) is most closely related to our current research, where the author specifically studied the role of experience in internet auctions. He argued that consumer learning, as measured by their "experience" level, drives the bidding process toward the outcomes predicted by theoretical auction research. This paper also uses eBay as its research context. Our paper, however, extends Wilcox (2000) in many ways. (1) We consider not just the learning process, but also the effect of desperateness that results when bidder demand is not satisfied in previous auctions. Our result indicates a contingent effect of bidder learning missing in Wilcox (2000). (2) More importantly, our data highlight "learning" in much greater detail: not only do we have the complete bidding history of each bidder (including the timing and amount of each bid), we also study the learning of bidders from previous loss, which is not captured by the "experience level" data used[1]. Other marketing research suggests that participation or experience itself is a learning process ("experiential learning", e.g. Armantier 2004). Therefore, our data allow far more detailed analyses of the learning process than found in previous studies.

There have also been a number of studies using experimental data to examine the role of learning in auctions, such as Guth et al (2003) which studied auction outcomes under both first-price and second-price rules. They found that, interestingly, learning does not drive bidding toward the benchmark solution. Beyond auctions, there is a large literature related to learning, such as organization learning (through exploration and exploitation) (e.g. March 1991), learning in the context of supply chain models (e.g. Valluri and Croson 2005), and consumer learning in marketing (e.g. Hogg and Lewis 2005). For example, Iyengar, Ansari and Gupta (2007) studied the role of consumer learning and its implications for service quality and usage. Amaldoss and Jain (2005), in their study of conspicuous consumption, discussed the role of consumer learning for monopolistic pricing policies. Overall however, these are less directly related to our current investigation which focuses on actual bidding data.

Our investigation is rooted in the work of Bapna, Goes, Gupta and Jin (2004), who offered a taxonomy of bidders. We use this taxonomy to distinguish the migration of different bidders and their effects, as well as the learning process of bidders as they migrate.

We propose that bidder migration could have two potential influences on later auctions. The first influence, which we shall call ***learning effect*** for simplicity, is related to the economics and marketing literature of consumer learning. Literature has identified two general types of learning: observational learning and experiential learning (Armantier 2004), and our study is specifically focused on the experiential learning of bidders (placing bids). Marketing literature also refers to the movement of bidders across auctions and how previous outcomes affect their probability of participation in later auctions (Ariely and Simonson 2003; List and Price 2005). Bapna, Goes, Gupta and Jin (Bapna, Goes et al. 2004) also suggest bidder learning effects, though only as a post-hoc analysis. To the best of our knowledge, systematic examination of this phenomenon is rather scarce; there is even less work from the perspective of auction sellers or discussions of how studying such phenomenon can affect the sellers.

Meanwhile, as long as a bidder's utility from consumption of a product is time dependent – which is almost a standard assumption in economics and finance – we propose that when bidders migrate to later auctions they are likely to increase their bid so as to obtain the product. This could, in turn, induce an upward pressure on the final price of later auctions. In our paper we call this ***desperation effect*** for simplicity. The empirical difficulty lies in separating two concurrent effects in the data. We shall attempt to tease out their different effects by using different measures of bidder migration, the details of which is discussed in the next section.

MEASURING BIDDER MIGRATION

In this section, we propose a system of measures for bidder migration. In general, we differentiate bidders in two dimensions: (1) whether they won or lost previously; and (2) whether they were evaluators in previous auctions. For the purpose of the current paper we measure bidder migration statically: we measure bidder migration after an auction has concluded, and we do not differentiate bidders who participated in three previous auctions vs. just one previous auction; they carry the same weight in our current set of measures. While this is a limitation, the simplistic measures used here are also more intuitive. Moreover, such detailed measurements will not result in significant difference in our estimation results since the length of time in our sample is not sufficiently long. We have included our set of extended measures of bidder migration in the appendix, however; and our models and results can be easily replicated under the new measures.

1. Defining Bidder Migrations

We measure bidder migration using several mutually exclusive measures, as we shall expand on, and the relationship among these measures can inform us about the learning vs. desperation effects that emerge when bidders migrate.

The concept of "evaluator" originates in Bapna et al (2004), where Bapna and his colleagues classified bidders into five categories:

1. *Early evaluators* – places just one maximum bid early in the auction
2. *Middle evaluators* – places just one maximum bid in the middle of the auction

[1] As indicated in Wilcox (2000) (page 373), the "experience level" data used in his paper only captures the number of times a bidder participated in auctions *and won*. Inherently, such measure does not consider participations without success.

3. *Opportunists* – late bidders
4. *Sip-and-dippers* – places two bids; one early and one revised bid late
5. *Participatory bidders* – bid throughout; early entry and late exit

Overall, evaluators spend much less monitoring cost in the auctions than the others. But as we discuss in Appendix 1, the results for early evaluator seems more distinctive than middle evaluators; therefore, in our paper, we define **evaluators** using the same measures that Bapna and his colleagues defined early evaluators, and definite the remaining bidders **non-evaluators**. More detailed discussions are in Section 5.

Here are some more notations before we proceed:

Λ_i : set of bidders for auction *i*

Λ_i' : set of non-evaluators for auction *i* (explanations below)

Λ_i'' : set of losing bidders for auction *i*

Our first definition of bidder migration, BM_i^1 (where BM stands for "Bidder Migration"),is the ratio between the number of bidders who lost and were non-evaluators in previous auctions, to the total number of bidders in the current auction:

$$BM_i^1 \equiv \frac{\sum_{j_i \in \Lambda_i} 1(j_i \in \bigcup_{\{-i|t_{-i}^1 < t_i^1\}} (\Lambda_{-i}' \cup \Lambda_{-i}''))}{|\Lambda_i|}$$

Where

i – auction *(-i:* other auctions for the same product*); j* – bidder*; t* – time*;* t^1 –auction end time*;* $j_i \in \Lambda_i$, where Λ_i is the set of bidders in auction *i* and $|\Lambda_i|$ denotes the number of unique bidders in that auction. 1(.) is an indicator function that takes a value of 1 if (.) is satisfied, and 0 otherwise.

The above diagram (Figure 1) is an illustration of BM_i^1. Note again that this measure is a static measure; each set indicates the bidders of that auction, regardless of how many bids they placed there. In this diagram, each oval or circle stands for an auction. The shaded circle is our auction of interest, and the other two ovals are auctions that end earlier than the end of the circle auction. So in the upper left auction, there are four bidders, in the lower left oval, there are 6 bidders, and so on. By BM_i^1, the focal auction (shaded) has a bidder migration index of 3/6=0.5.

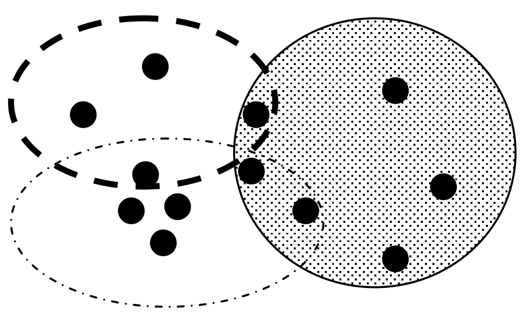

Figure 1: Bidder Migration Index

The second measurement of bidder migration focuses on evaluators who lost previously. Specifically, our second measurement of bidder migration is:

$$BM_i^2 \equiv \frac{\sum_{j_i \in \Lambda_i} 1(j_i \in \bigcup_{\{-i|t_{-i}^1 < t_i^1\}} (\overline{\Lambda}'_{-i} \cup \Lambda''_{-i}))}{|\Lambda_i|}$$ where $\overline{\Lambda}'_{-i}$ is the complementary set of Λ'_{-i}

The third measurement focuses on bidders who won previously, and are non-evaluators:

$$BM_i^3 \equiv \frac{\sum_{j_i \in \Lambda_i} 1(j_i \in \bigcup_{\{-i|t_{-i}^1 < t_i^1\}} (\Lambda_{-i} \cup \overline{\Lambda}''_{-i}))}{|\Lambda_i|}$$

And the last measurement focuses on bidders who won previous and were evaluators:

$$BM_i^4 \equiv \frac{\sum_{j_i \in \Lambda_i} 1(j_i \in \bigcup_{\{-i|t_{-i}^1 < t_i^1\}} (\overline{\Lambda}'_{-i} \cup \overline{\Lambda}''_{-i}))}{|\Lambda_i|}$$

To summarize, we classify bidders along the above-mentioned two dimensions, in the following manner:

Table 1: BM1-BM4

	Non-evaluators	Evaluators
Losers in prev. auctions	BM_i^1	BM_i^2
Winners in prev. auctions	BM_i^3	BM_i^4

Note that all bidders in a given auction will be placed in the above 2×2 just once. For instance, if Joe lost in a previous auction *and* was an evaluator in that auction, he will be counted when calculating BM_i^2, but not any of the other three measures. If Linda won a previous auction and was not an evaluator there, she will be counted in the calculation of BM_i^3, but none of the other three.

2. Linking Bidder Migration Measures to Price Effects

As we argued previously, two potential effects that could occur when bidders migrate are the learning effect, which we hypothesize to exert a downward pressure on prices; and the desperation effect, which would likely result in higher prices. We mentioned that the difficulty lies in teasing out the effect of these two effects. In this section, we shall argue that, using the four measurements as defined above, we can tease out these effects.

As we mentioned above, the distinction between winners and losers is to focus on the "desperation effect" whereby bidders are likely to bid higher because of unfulfilled demand. On the contrary, the difference between evaluators and non-evaluators are to expose the "learning effect". Hence, we have the following results which will inform our model building:

1) The difference between BM_i^1 and BM_i^2 can be regarded as a proxy of learning effect for bidders who lost previously; and $(BM_i^3 - BM_i^4)$ the learning effect for bidders who won previously. In other words, in Table 1, the *difference across columns is the learning effect after controlling for desperation effects*.
2) By the same token, the difference between $BM_i^1 - BM_i^3$ can be considered a proxy of desperation effects for non-evaluator bidders; and $(BM_i^2 - BM_i^4)$ the desperation effect for evaluators. In other words, in Table 1, the *difference across rows is the desperation effect after controlling for learning effects.*

In our model specifications, we will first use these measures independently but will later use the above differences to study the price effect of desperation versus learning.

DATA AND EMPIRICAL EVIDENCE OF BIDDER MIGRATION

Our data include the complete bidding history of 27 products on eBay during a three-month period in 2002. There are over 10,000 auctions in our dataset. For all these products, we found consistently more than 50% bidders engage in auctions in the same category more than once. Out of over 10000 auctions, the bidder pool of only 5.79% auctions are purely made of first-time bidders.

The following is a box plot of $BM_i^1 - BM_i^4$ in our dataset (Figure 2):

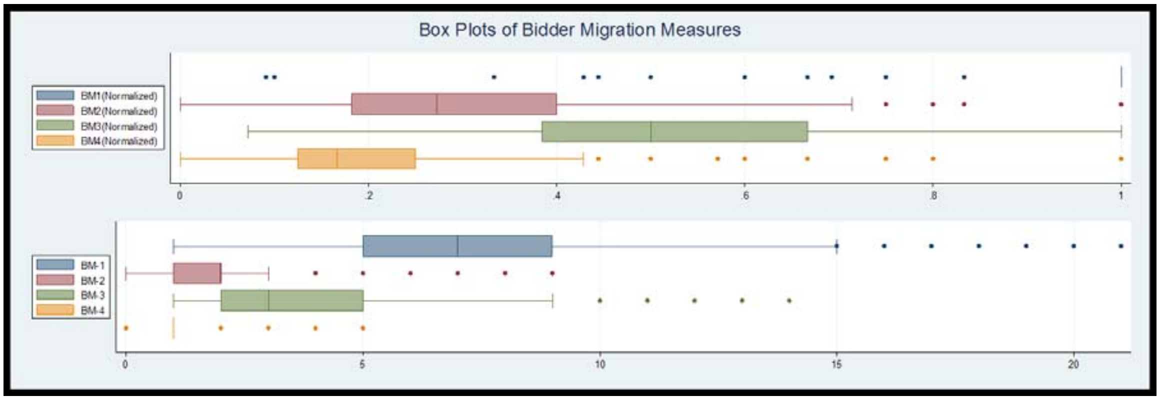

Figure 2: Box plot of bidder migration measures

The graph on the last page (Figure 3) is an illustration of bidder migration index across different products in our dataset using the TreeMap software developed by the Human-Computer Interaction Lab (HCIL) at the Department of Computer Science, University of Maryland College Park[2]. Each "cell" indicates an auction; in addition the warmer the color, the higher the value of bidder migration index for that auction. This Treemap is calculated according to BM_i^1.

PRICE EFFECTS OF BIDDER MIGRATION

1. Calculating Bidder Migration Indices

The first measurement of bidder migration, BM_i^1, distinguishes between different types of bidders according to literature on bidder heterogeneity (Bapna et al 2004). This measurement is also interesting from a theoretical perspective because although generally a bidder's unfulfilled demand should have an impact on later auctions, if a bidder participated in an earlier auction without sufficiently strong motivations to win in those (for instance, just to see how auction works), they are not very different from individuals who participate for the first time (non-migrating bidders). By focusing on bidders that are not evaluators – serious bidders –the price impact of bidder migration will only be stronger.

In calculating BM_i^1, we focus on "early evaluator" because out of the five categories of bidders, early evaluators are the least engaged in an auction. Another reason is that the distance of this group of bidders from others is much more distinct than middle evaluators, especially if we consider both the 1999 and 2000 samples in Bapna et al (2004). (See appendix about the specific definition of "early evaluator" as well as Table 4 and Table 5 from Bapna's paper.) Therefore, in our analysis, we *exclude* the following bidders as evaluators when calculating BM_i^1 (please see appendix for details; this leads to a conservative estimate of the impact of bidder migration):

1) Number of bids is smaller than 2 (1.11 + 2*0.39);

2) Time of first bid is smaller (earlier) than 1.97+2*0.99 = 3.95 (time normalized to 10);

[2] http://www.cs.umd.edu/hcil/treemap/

3) Time of last bid smaller (earlier) than 2.09 + 2*0.95= 3.99 (time normalized to 10).

In other words, we count a bidder as a non-evaluator in an auction if he or she places more than 2 bids in the auction AND if the first bid is placed earlier than 3.95 (out of a auction length of 10) AND if the last bid is earlier than 3.99.

To estimate the price effect of bidder migration using $BM_i^1 \sim BM_i^4$, we estimated different specifications using the GLM (Generalized Linear Models) framework and select a model with best statistical fit through BIC (Bayesian Information Criterion). More details of this step is discussed in the next section

2. Model Specification and Selection

Our dependent variable is the price of auctions. Since the distribution of price in our sample is quite dispersed, we take the logarithm of prices as the dependent variable. Independent variables are the typical variable in online auction studies, including seller experience (logarithm); starting bid; duration of auctions; number of bids, and bids per person. We also include dummies for product categories as additional explanatory variables. The results that we report here do not include seller experience or duration, since they consistently turned out insignificant; however it should be noted that results on our key explanatory variable – bidder migration measures – are robust to the inclusion or exclusion of these variables. In fact, using BIC (Bayesian Information Criteria) as the model selection criteria, we always favor models without these two explanatory variables.

For model specification, we tested several specifications of the Generalized Linear Model, which is a generalization of the classical ordinary least squares[3]. Our results indicate that Gamma distribution with log link function outperforms other specifications with the lowest BIC score. We will therefore focus and report the results from this specification.

More specifically, our model is

$$\log \text{Price} \sim Gamma$$

$$E(\log \text{Price}) = \text{g}^{-1}(\alpha * BM + X\beta)$$

Where $X = \begin{pmatrix} \text{Starting bid} \\ \text{Number of Bids} \\ \text{Bids per person} \\ \text{Category dummies} \end{pmatrix}$ and BM are the corresponding measures for bidder migration, which we specify below. The models are then estimated using the -glm- procedure in Stata 10.

To understand the price effect of bidder migration, we studied two sets of statistical models. In the first set of models we use BM_i^1 through BM_i^4 as an independent variable, entering the above equation direction to estimate the effect on price. In the second set of models, we use the difference across columns or rows in Table 1 to better capture the learning effect versus desperation effect. Results from these two sets of models are consistent with each other. We shall briefly report the first set of results and then focus on the second set for discussion.

3. Estimation Results 1: BM_i^1 through BM_i^4 as independent variables

In the first set of models, we directly use the four measures as independent variables. The results are presented below.

Table 2: Estimation Results 1

	With BM_i^1	With BM_i^2	With BM_i^3	With BM_i^4
Log(start bid)	.04***	.04***	.04***	.04***

[3] OLS is an instance of GLM with identity link and normal distribution.

Log(bids per person)	-.03***	-.04***	-.04***	-.04***
Log(number of bids)	.20***	.21***	.21***	.21***
Intercept	.59***	.56***	.56***	.57***
BM_i^1	-.06*			
BM_i^2		0.5***		
BM_i^3			-.05*	
BM_i^4				-.01

(Legend: * p<0.05; ** p<0.01; *** p<0.001)

As we discussed on page 4, by studying the difference across adjacent cells or definitions in the "matrix" of bidder migration measures (Table 1), we can incrementally study the effects of learning and desperation while controlling for the other. For instance, BM_i^1 and BM_i^2 both take into account bidders who lost in previous auctions (holding the "desperation effect" constant), and their difference highlights the marginal effect of learning. BM_i^1 and BM_i^3, on the other hand, both consider non-evaluators (controlling for the "learning" effect), hence their difference accounts for the marginal contribution of the "desperation effect". By contrast, the difference between BM_i^1 and BM_i^4, or BM_i^2 and BM_i^3, does not allow a clean interpretation of the comparative effect of learning and desperateness.

As we can see from Table 2 above, the estimation results of other variables (controls) are quite stable across these four model specifications. For the measures on bidder migration, however, there is a difference. Note that with BM_i^4 the price effect is not sigificant – these are the bidders who are only evaluators and who had won previously. In other words, neither learning nor desperation effects show up for this group. BM_i^2, by contrast, are the bidders who are evaluators (not that serious in their participation) but never won before. This is the group where learning effect should dominate, since their desperateness of obtaining the product is more obvious. And this is confirmed by the positive and significant coefficient in Table 3. BM_i^3, which focuses on nonevalutor-winners, dims the desperateness but embodies the learning effect, shows a negative coefficient: they are not desperate to get the products, and the learning from being an active participant in the auction process is associated with a negative price for later auctions. All these are consistent with our predictions.

However, interpretation is less clear for BM_i^1, which is the percentage of bidders who lost and were non-evaluators seriously. While it appears safe that the negative coefficient indicates the learning effect to dominate the desperation effect, we note that in this set of models, all these measures enter the estimation separately and we are less clear in teasing out different price impacts of bidder migration. Hence we move on to the next set of models, with the same specification but slightly different bidder migration measures, to estimate and empirically separate these two effects concurrently. Our rationale for this specification has been discussed in Section 3.2.

4. Estimation Results 2: Difference between Measures to Capture Different Effects

Again, we now turn to incorporate multiple bidder migration measures in one model to tease out the relative effects of learning vs. desperation. To briefly summarize our previous discussion, in Table 1 –

1. *The difference across columns is the learning effect after controlling for desperation effects.*
2. *The difference across rows is the desperation effect after controlling for learning effects.*

We now estimate the same specification of generalized linear model but with the differences as independent variables. The estimation results are as follows:

Table 3: Estimation Results 2

	With $(BM_i^1 - BM_i^2)$	With $(BM_i^3 - BM_i^4)$	With $(BM_i^1 - BM_i^3)$	With $(BM_i^2 - BM_i^4)$
Log(start bid)	.04***	.04***	.04***	.04***
Log(bids per person)	-.03***	-.04***	-.04***	-.04***
Log(number of bids)	.20***	.21***	.21***	.21***
Intercept	.58***	.56***	.56***	.57***
$(BM_i^1 - BM_i^2)$	-.04***			
$(BM_i^3 - BM_i^4)$		0.00		
$(BM_i^1 - BM_i^3)$			-.00	
$(BM_i^2 - BM_i^4)$				-.02*

(Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$)

Again, we argued that lose/win denotes the 'desperateness' while evaluator/nonevaluator denotes 'learning' effect. Therefore the coefficient on $(BM_i^1 - BM_i^2)$ indicates the learning for bidders who lost previously; that on $(BM_i^3 - BM_i^4)$ indicates the learning for those winning bidders. From the results we see that the learning effect for bidders who lost previously are much stronger (-.04) then for bidders who won before (0, nonsigificant).

On the other hand, $(BM_i^1 - BM_i^3)$ denotes the "desperation effect" for serious bidders who actively participate in the bidding process of previous auctions; and $(BM_i^2 - BM_i^4)$ denotes the desperation effect for evaluators. From the results in Table 3, we see that serious bidders (nonevaluators) can keep their "cool" and not be overwhelmed because they lost previously; by comparison, evaluators are more likely get desperate for the products, hence increase the price for later auctions.

IMPLICATIONS

Studying the migrating behavior of bidders has significant implications for practitioners in auctions. We propose three potential applications of this measurement.

First, bidder migration goes beyond the traditional feedback score that has been widely used in online auctions. These feedback scores, particularly those used on eBay, changes only when a user completes a transaction; after each auction has completed, the feedback scores of only two users will change: that of the seller and of the winning bidder. In addition, feedback score is a conglomerate number that does not distinguish the role of the user or the feature of the product. By contrast, bidder migration captures important information about bidders' previous actions that have not been made available to sellers.

Bidder migration provides a new perspective for sellers to design their auctions. When to start an auction, when to end an auction, and how high to set the starting bid and/or reserve price, all these decisions will be improved if the seller has a better understanding of the group of individuals who is likely to participate in his/her auction. In other words, information about previous auctions will be beneficial to the auctioneers to learn about their potential "customers" (i.e. bidders). Furthermore, having bidders' migration information could improve sellers' ability to dynamically predict the price evolution, as well as the final outcome (Wang, Jank et al. 2006).

For instance, when a seller is ready to set up a new auction, the platform (such as eBay) can provide as value-added service information regarding bidder migration activities in the category where the seller is planning to list his auctions. When there is very significant migration in that category (or a related one), sellers might consider setting a very low starting or reserved price so as to attract bidders. When there's very low migration, setting the starting or reserved price low might result in less-than-desirable final prices.

Secondly, we argue that bidder migration can be used as a mechanism for customer segmentation, or "*bidder segmentation*". Segmenting customers enables sellers to extract higher levels of rent from transactions, as documented by the price discrimination literature in economics and marketing literature; we argue that this is also feasible for sellers who use the auction format. For instance, from our analysis we find that the bidders who are serious in their bidding strategy (as measured by BM_i^1 and BM_i^3) exert downward pressure on the final auction prices. Hence, for auctioneers with multiple items, it would be advisable for them to try to reduce the number of serious bidders in one auction, thereby reducing the BM_i^1 or BM_i^3 index. This can be achieved either by setting up multiple concurrent (identical) auctions, or even reaching out to these customers using targeted advertising, and offer them the opportunity to buy outside the auction. Alternatively, bidders can be offered discount on future fixed-price auctions. Although much remains to be done to make this practical, we believe that segmenting bidders could be potentially profitable for sellers as well as efficiency-improving.

While the "traditional" segmentation mechanisms such as customer demographics or price sensitivity is not directly observable for auctioneers – since it raise concerns for customer privacy, and might not be accurate anyway – bidder migration behavior can be provided to auctioneers by platforms such as eBay as a value-added service. In fact, while customer demographics can change frequently (e.g. change in job status and personal life) and are unlikely to be always up-to-date, their participatory behavior are more likely to reflect their current underlying characteristics. Segmenting bidders on behavior can be considered as a generalization of segmenting on demographics, only more accurate.

Another potential application of bidder migration is to detect shill bidding. If a bidder is consistently migrating across auctions, never wins an auction, and shows up consistently in the same seller's auction, this bidder is more likely to be a shill bidder than the average bidder.

CONCLUSIONS AND FUTURE RESEARCH

We selected eBay as the context for our analysis due to the following reasons: eBay is the largest C2C online auction platform and attracts a lot of attention; thus, our results can potentially generalize to a wide range of consumers; also, eBay offers many product categories, which makes it possible to study bidder learning across a wide variety of different product types (e.g. one-of-a-kind products vs. commodities). Moreover, bidding data can be readily obtained from eBay (in contrast to other auction sites) which is essential for measuring bidder migration and learning.

Our current paper presents some of the first empirical evidence of how bidder movements across auctions impact the outcome of later auctions. More specifically, we identified two potentially confounding effects: the **learning effect** where bidders learn to become more sophisticated bidders, hence driving down the price of later auctions; and the **desperation effect** wherein bidders, in a hope to obtain the product that they previous couldn't win, tend to increase the prices. We empirically verified these two different effects using bidding history data from eBay. Moreover, we showed that these two price effects are contingent upon each other: learning effects are stronger for bidders who are evaluators, and the desperation effect is more evident among bidders who are evaluators. Last but not least, our research has proposed measures for bidder migration which can be easily adopted by auction platforms and then provided to market participants as a value-added service.

This research is consistent with an emergent stream of literature on the competition among auctions. We argue that other than sellers and products, bidders constitute another important linkage among auctions, which has unfortunately received very little study in the past. We hope that the measures we proposed in this paper as well as the results that we derived from data analysis provide the first step in the direction of research in this fruitful area. Auctions can be related to each other even through the bidders; therefore, early auctions provide valuable information about the bidders for later auctions; and these auctions can be for the same product, or even for related, complementary products. Incorporating such information can have significant value for both researchers and for practitioners. In a sense, such information-transmission illustrates that the relationship among auctions need not always be competitive, but could very well be at least partially complementary.

In the appendices (Appendix 2 and 3) to this paper, we propose more detailed measures of bidder migration that takes into account bidder history (i.e. the number of times that they participated in earlier auctions) as well as the time length since their prior participation, which is meant to capture a decay effect of learning. We are currently updating our analyses with these more detailed measures.

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APPENDIX 1: DEFINING “EARLY EVALUATORS”

To define “early evaluators” in our sample, we refer to Table 4 and 5 in Bapna (2004):

Middle evaluators are quite distinct from Opportunists in 1999 sample but much less so in their 2004 sample, especially the mean of the “Time of Last Bid”. On the other hand, “early evaluators” seems to be quite distinct in both samples. Therefore, to be conservative in our estimates, we focus on *early evaluators* when calculating our bidder migration measures.

More specifically, a bidder is considered an early evaluator in an auction if (mean + 2 times standard deviation for 1999 or 2000, whichever is smaller):

1) Number of bids is smaller than 2 (1.11 + 2*0.39)
2) Time of first bid is smaller (earlier) than 1.97+2*0.99 = 3.95 (time normalized to 10)
3) Time of last bid smaller (earlier) than 2.09 + 2*0.95= 3.99 (time normalized to 10)

Table 4. 1999 Data Cluster Centers (Time is Normalized on a 1 to 10 Scale)						
		Cluster Name				
Cluster Dimensions	Descriptive Statistics	Early Evaluators	Middle Evaluators	Opportunists	Sip-and-DIpper	Participators
Number of Bids	Mean	1.11	1.20	1.7	2.12	3.86
	Standard Deviation	0.39	0.55	0.58	0.32	1.11
	Skewness	4.14	3.10	2.20	2.40	1.58
	Kurtosis	19.25	10.64	4.31	3.80	2.79
Time of First Bid	Mean	1.97	4.45	8.40	2.13	1.47
	Standard Deviation	0.99	1.33	1.09	1.50	1.08
	Skewness	–0.46	–0.45	–0.56	0.59	0.87
	Kurtosis	–1.11	0.59	0.82	–0.53	0.13
Time of Last Bid	Mean	2.09	4.77	8.72	8.26	8.59
	Standard Deviation	0.95	1.01	1.01	1.46	1.29
	Skewness	–0.60	0.59	–0.25	–0.98	–1.02
	Kurtosis	–0.73	–0.34	–1.22	0.67	0.81
Number of Bidders		575	524	558	283	141

(Source: Bapna et al 2004)

Table 5. 2000 Data Cluster Centers (Time is Normalized on a 1 to 10 Scale)						
		Cluster Name				
Cluster Dimensions	Descriptive Statistics	Early Evaluators	Middle Evaluators	Opportunists	Sip-and-DIpper	Participators
Number of Bids	Mean	1.24	1.40	2.45	5.99	15.56
	Standard Deviation	0.51	0.81	0.82	1.72	6.12
	Skewness	2.10	2.48	1.33	0.82	1.70
	Kurtosis	3.54	6.92	2.13	0.22	2.63
Time of First Bid	Mean	1.99	7.55	1.22	1.93	1.50
	Standard Deviation	1.49	1.55	1.10	1.85	1.57
	Skewness	0.63	0.14	1.15	0.79	1.16
	Kurtosis	–0.79	–1.22	0.77	–0.77	0.80
Time of Last Bid	Mean	2.53	8.08	8.02	7.53	7.81
	Standard Deviation	1.88	1.56	1.41	2.41	2.19
	Skewness	1.06	–0.28	–0.16	–0.85	–0.82
	Kurtosis	1.32	–1.30	–1.06	–0.37	–0.69
Number of Bidder		409	362	101	127	41

(Source: Bapna et al 2004)

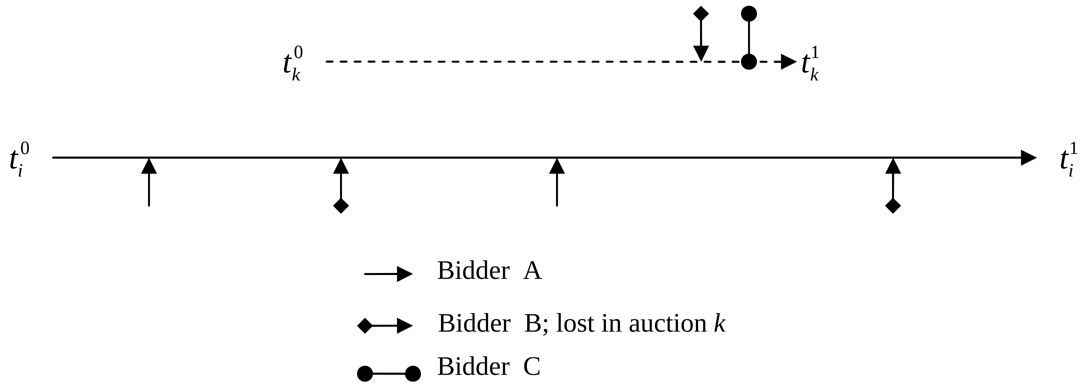
APPENDIX 2: EXTENDED MEASURES FOR BIDDER MIGRATION

It should be noted that the definitions in the paper above do not capture multiple losses in the past, because we used "union"; for instance, if the bidder loses in two previous auctions when they come to the third auction, he or she would count equivalently in the calculation of the migration index of the third auction as another bidder who just lost once previously. More importantly, both the learning effect and unfulfilled-demand effect has a time dimension: the learning could be decaying over time, and the "desperateness" from unfulfilled demand is also likely to either diminish or exacerbate over time. Hence, in this section, we shall extend the above measures to incorporate these issues. But since these issues equally apply to $BM_i^1 - BM_i^4$, for simplicity, here we only discuss these extensions using BM_i^1.

To take into account number of times they participated previously, we propose a fifth measurement of bidder migration as simply the number of times that all bidders in the current auction have bid in previously concluded auctions, or

$$\underline{BM}_i^1 \equiv \sum_{j_i \in \Lambda_i} \sum_{\{-i|t_{-i}^1 < t_i^1\}} 1(j_i \in \Lambda_{-i})$$

As a further extension, consider the following time line that an auction progresses through:



Given that certain other auctions could start[4] during this process, another measurement of bidder migration could be proposed as a function of time. Simply put, whenever a bid is placed, we find out how many times the originator of this bid has participated in previously concluded auctions, and add it to the same measure on all *other* bidders in the current auction. Mathematically,

$$\overrightarrow{BM}_i^1(t) \equiv \sum_{j_i \in \Lambda_{it}} \sum_{\{-i|t_{-i}^0 < t\}} 1(j_i \in \Lambda_{-it})$$

where Λ_{it} is the set of bidders of auction *i* at time *t* and 1(.) is an indicator function that takes a value of 1 if (.) is satisfied, and 0 otherwise.

All measures above can be further enhanced to include a term to allow for discounting: the longer the end of the earlier auction, the smaller the impact (or learning effect) that remains; alternatively, the notion of discounting suggests that the effect from ancient bids is already integrated into more recent bidding behaviors. Assuming an exponential discounting rate of *r*, the discounted measure of bidder migration of auction *i* at time *t* can be written as:

$$\overline{\overrightarrow{BM}}_i^1(t,r) \equiv \sum_{j_i \in \Lambda_{it}} \sum_{\{-i|t_{-i}^0 < t\}} e^{-rt} \cdot 1(j_i \in \Lambda_{-it})$$

These extensions allow for more sophisticated statistical modeling as well as better interpretation of analytical results. For simplicity however, in the following data modeling we would focus only on the static, non-discounted measures of bidder migration ($BM_i^1 - BM_i^4$) as a first step in this direction.

APPENDIX 3: DEFINING BIDDER MIGRATION FROM A BIDDER'S PERSPECTIVE

We can also define bidder migration from a bidder's perspective. The advantage of these measures is that we can observe the change of bidder behavior along their migration routes. Simply speaking, a migration index for a bidder is the number of ***concluded*** auctions that a bidder has participated in. It is a number that varies over time. Similar to the measures above, we can also measure a bidder's migration index in several ways.

It should be noted that a bidder's migration index is distinctly different from his or her feedback score, which measures the number of positive feedbacks provided to him or her by other users. The feedback score is used by eBay as a measurement of bidder reputation. Important as it is, in many situations the feedback score is quite lacking in providing sufficient

[4] Other auctions can also *conclude* during this process, and a current bidder in the focal auction could have one more lost / won auction in his / her record, and this would have an effect on some of the measures.

information about a bidder to a seller: having a hundred positive feedbacks in buying paper clips probably is not convincing enough when the next auction is for an HDTV.

Bidder migration index, by contrast, provides a potentially much more relevant measure for auction sellers. By defining bidder migration on different levels (product level, category level, and so on), auction sellers can have a much better understanding of his bidder pool and better assess the transaction risks.

Before we delve into the details of this second set of measurements of bidder migration, it would be worthwhile to consider the relationship between defining migration from a bidder's perspective versus from a seller's perspective. Theoretically, if we have the complete transaction history records of all auctions that all bidders have participated in, these two sets of measurements would be equivalent; we should be able to derive one measure from the other. If we have all the measures for all current bidders in an auction, we can calculate the index for that auction. If we know all the bidder migration indexes of all auctions that a bidder participates in and how they change relative to his bidding time, we can also calculate a bidder's migration index.

However, conditions for such equivalence are very difficult to satisfy. In particular, for researchers, we are restricted by the amount of information we will be able to gather. We are only able to gather bidding history of auctions in certain categories for certain products, during a certain period of time. Although such practical limitations prevent us from a full understanding of the dynamics of bidder learning, our study from auctions' perspective provides a first step in that direction. Moreover, this situation is similar to what auction sellers are faced with, so in our current study, our focus would be bidder migration from seller's perspective. Nonetheless, for the sake of generality, in this section we briefly outline measurements from the bidder's perspective. For auction platform such as eBay however, these measures can be easily implemented and provided as a value-added service for merchants who wish to better manage their auctions.

A *bidder's* migration index is the number of **previously concluded auctions** that a bidder has participated in at the time he or she places a bid in one particular auction. Given the observation that bidders could be participating in multiple auctions for one product simultaneously, this index is a value that changes over time for each bidder; more specifically, it changes whenever an auction that the bidder participates in ends. Since we do not have observation of bidders when they do not submit a bid, in our current dataset we can only look at migration based on actual bids placed. Similar to $BM_i^1 - BM_i^4$, the measure from the bidder's perspective can also be enhanced with a time dimension to allow for more detailed statistical modeling and better interpretation of results.

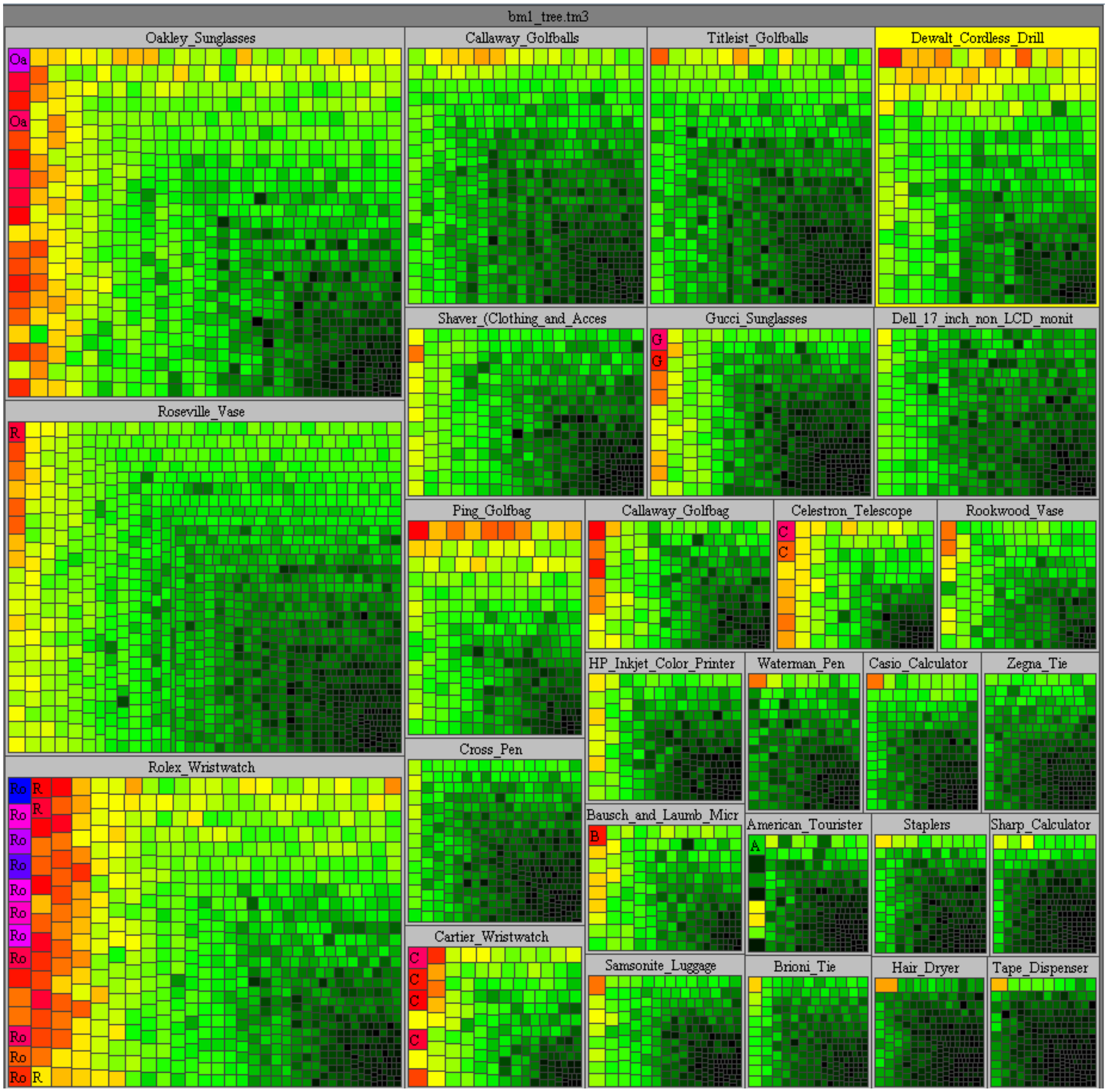
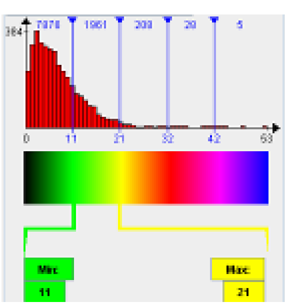


Figure 3: TreeMap

Legend:



Brighter color or cells to the upper left corner in each category indicates higher level of bidder migration. Darker colors or cells to the lower right corner indicate lower level of migration. We can see that bidder migration is, on average, highest for luxury items such as Rolex or Cartier wristwatches and for Oakley sunglasses. On the other hand, it is very small for tape dispensers or calculators.