Price Dynamics In
Virtual World Auctions

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Abstract:
Virtual worlds like World of Warcraft and Second Life are slowly becoming recognized by researchers as ideal testing grounds for their theories. The unprecedented control over the world’s dynamics and the easy access to its data make them ideal for observation and controlled experiments. Do results from these worlds, however, have bearing on the physical world? While the agents in these worlds are indeed controlled by humans, the characteristics of these worlds differ from the physical world in many ways, not the least of which is in physics.

One way to begin to answer this question is to analyze the behavior of bidders and sellers in virtual currency auctions. Specifically, this paper examines auctions in World of Warcraft and argues that buyers and sellers both value the game’s currency and price items consistently. The paper then briefly explains why the auction mechanism differs from eBay’s enough to render useless the techniques employed to analyze eBay auctions, and it concludes with a justification of why researchers should pay more attention to virtual worlds.
1 Introduction

Auctions sites like eBay and Amazon have initiated a shift in the way consumer behavior and auction theory are studied by allowing the examination of vast amounts of data. In a given year eBay hosts millions of auctions on thousands of different items, ranging from collectable coins to cars to houses. Through a crawler program on their website it is possible for researchers to get access to this auction data.

Some of this data has been used to examine auction theory — for example, there is now extensive literature on last-minute bidding in eBay auctions, such as Ariely, Ockenfels and Roth [2] and Roth and Ockenfels [18]. There is also literature on consumer behavior, including studies in brand loyalty and the market price of product features, such as Vogt and Xu [23]. This sort of information is useful to companies in making decisions about the future development of their brand lines.

There are, however, several drawbacks to data from eBay. One of the problems facing researchers is how to properly take into account the information asymmetries between buyers and sellers. Unlike physical auctions, buyers cannot examine the items to judge their quality — the only information they have is in the description on the website. On the one hand this is good because the consumer has no more information than the economist, but on the other hand this is bad because it might inhibit efficient operation of these markets. For a study on this latter phenomenon, see Bajari and Hortacsu [4].

One potential source of ample auction information for completely homogenous goods is World of Warcraft, a Massively Multiplayer Online Role Playing Game (MMORPG) with over ten million active players. At any given moment there are well over a million auctions being run in an in-game auction house.

The advantage of these auctions is that there are absolutely no information asymmetries — though there are vast differences between different kinds items, every item of the same kind is perfectly identical, and information on every item is common knowledge — one can view its ap-
pearance and characteristics simply by mousing over it. Data also exists on every agent in the
game, including, among other things, how much time they have played and their current wealth.
This latter data is not publicly available, but it is tracked by the game’s creator, Blizzard Enter-
tainment, and could in theory be made available to an economist who approached them. The
combination of personal wealth data with bidding behavior could let economists study auctions
and consumer behavior in new ways. Furthermore, if economists teamed with game developers, it
would be possible to conduct wide-scale experiments in a way impossible in the physical world.
Consider, for instance, changing the drop-rate of an item, which is equivalent to changing the sup-
ply. The experimenters could ensure that absolutely nothing else was changed in the economy but
that one parameter, which would allow them to properly study its effects.

This paper attempts to argue that World of Warcraft is suitable for economic analysis. At
several points in-game auctions are compared to eBay auctions. This is made difficult, however,
because Blizzard Entertainment does not have an economist on staff, and so by poor mechanism
design the auction house essentially functions as a posted price market with 96% of auctions sold
via a Buy-It-Now option. Thus techniques from empirical auction theory could not be applied
to World of Warcraft auctions. There are, however, still claims that bidders value the game’s
currency and price items highly consistently and that sellers list items for what appear to be utility
maximizing prices.

The paper begins with a review of auction theory literature in Section 2, specifically focusing
on analysis of eBay auctions. There is then a brief introduction to the game of World of Warcraft
in Section 3, the data in Section 4 and the market in Section 5. Section 6 describes what sort of
behavior we would expect in these auctions, followed by empirical exercises arguing that partici-
pants behave rationality in Section 7. Finally, a comparison is made to eBay in Section 8, a brief
argument for the value of auction theory is made in Section 9, and the paper concludes in Section
10.
2 Literature Review

The study of whether the seller in an auction behaves rationally begins with defining how a rational seller should behave. Vickrey [22] began this study by computing optimal bidding strategies and expected seller revenue in a variety of auction models. Using an independent private-value model with exogenous entry, he derived a revenue equivalence relation for multiple auction models, concluding that all auction models he examined yield identical equilibrium revenues.

This revenue equivalence relation was extended by Myerson [17] to include all possible private-value auction formats with risk-neutrality, independent private-values, and symmetric value distributions. Myerson [17] and Milgrom and Weber [16] also extended the analysis to common-value auctions and concluded that, under similar assumptions, revenues could be maximized by a second price auction with an optimally set reserve price. They note, however, that calculating the revenue-maximizing minimum bid is difficult because it requires knowledge of the bidders’ value distributions, which must be estimated from bidding data.

While these early papers led to strong comparisons of different auctions models, their results were eventually questioned. Harstad [9] examined what would happen if, instead of a fixed number of bidders, the number of bidders responded endogenously to the expected profitability of an auction. He found that in a common-value setting with costly entry, more bidders will enter an auction with a higher expected profits than one with lower expected profits. Equilibrium expected revenue, however, is inversely related to the number of participants — with limited participation each participant is more likely to win the auction and thus is willing to enter for a lower expected profit.

Levin and Smith [12] extended this treatment and analyzed both private-value and common-value settings. The paper concluded that in a private-value setting bidders will enter until the expected profit to each is zero. Thus it is optimal to set a zero reserve price, as the bidders will naturally maximize seller revenues. In a common-value model, however, it is in the seller’s best
interest to limit the number of bidders, and so optimal behavior will be to set a reserve price to discourage entry. The former conclusion is reaffirmed by Bulow and Klemperer [5], which shows that in a private-value setting the revenue to the seller is strictly higher with N+1 bidders than with N bidders. Furthermore, the difference in revenue between having N+1 bidders and N bidders is greater than the difference in revenue between having N bidders with an optimal reserve price and having N bidders with no reserve price. Because a reserve price discourages entry, it is thus optimal for the seller to set a zero reserve price.

Bajari and Hortacsu [4] attempt to test the theories on common-value auctions with endogenous entry using eBay data. On eBay, the seller is given the ability to set a public reserve (minimum bid) or private (hidden) reserve price. Bajari and Hortacsu attempted to determine which mechanism yielded the highest revenues. They examined 516 auctions for mint-proof coins. They found that, in accordance with the existing theory, a low minimum bid encouraged entry. They also found that the number that the number of bidders had a negative effect on the bid amounts: the expectation of one additional bidder decreases bids by roughly 3.2%.

Hong and Shum [10] analyzed construction procurement auctions and found for a large subset of their data that average procurement cost was strictly increasing with the number of bidders. This result supports the conclusion of Bajari and Hortacsu [4]. This was not true, however, for all of their observed auctions. They note that the theory is unclear on how competition affects bidding in a common-value setting. On the one hand a larger number of bidders increases competition and thus encourages more aggressive bidding, but on the other hand increasing the number of bidders increases the risk of the winner’s curse, which causes bidders to shade their bids. In many but not all cases the winner’s curse has the greater effect.

Song [19] questioned the Bajari and Hortacsu [4] model because it assumes that the observed bidders in an auction were all the potential bidders who were willing to pay the reserve price. Song notes that this is not a realistic assumption because bids are placed sequentially. As the price for an item rises, early bidders will be priced out of the auction, and potential bidders who would have
been willing to pay the initial reserve price but not the new price will have their bids censored.

Athey and Haile [3] propose a nonparametric auction model that could be applied to second price auctions. All previously listed papers made a priori assumptions about the distribution of bidders values, while a nonparametric model allows for many fewer assumptions, including allowing for bidder asymmetry. Previous work on nonparametric modeling of the value distribution was for first-price auctions, and one of the express purposes of this paper was to develop a model compatible with eBay. They show that the value distribution can be identified in an independent private value situation from the auction ending prices alone. The same could not be said for a common value situation, but they did conclude that in the presence of some exogenous variation in the number of potential bidders allows a test of whether an item has private or common value.

Song [19] attempts to improve upon the Athey and Haile [3] paper by removing the required assumption that the number of potential bidders willing to pay the reserve price is known. Athey and Haile [3] allow for this number of bidders to be randomly determined, but it is not, again because of bid censoring. Song develops a new identification method using nonparametric modeling that makes it possible to determine the underlying value distribution without knowing the number of potential bidders. This is possible if one knows any two valuations of which the rankings from the top are known. It can be shown that a distribution of independent and identically distributed random variables can be determined from any two order statistics, even if the size of the sample is unknown. Song then runs a simulation designed to resemble bidding on eBay and finds that her order statistics method does a good job identifying the value distribution. She also examines actual eBay data and finds that her model fares well there as well.

Adams [1] improves upon Athey and Haile [3] by adding a way to use instruments to identify the number of potential bidders. Thus the Athey and Haile [3] model can identify the value distribution in the same manner as the Song [19] model without having to know two order statistics, which in practice is difficult. The second order statistic is always the sale price in an English auction, but another order static cannot necessarily be found. The third highest bid could be the third
order statistic, but it’s possible that the truly third highest potential bidder has their bid censored by discovering the auction after the second highest bid had been placed.

Adams uses this model to estimate the value distribution for Chevrolet C5 Corvettes and then calculates the optimal reserve prices. He calculates both the optimal reserve price for a one-shot auction and if the seller considers the possibility of resale (listing the car again in a week). He finds that sellers set their minimum bids close to the optimal dynamic (considering re-listing) reserve. Adams also finds that the results of an OLS regression overestimate the value estimate for items compared to the order statistics method.

Several other papers examine demand for items on eBay to determine if sellers behave optimally. Lucking-Reiley [13] examines data from eBay coin auctions using OLS regressions and determines that minimum bids and reserve prices have positive effects on the final auction price. The minimum bids, however, only have a positive effect when they are binding to a single bidder — in other words, when only one bidder is above the minimum bid. This is in accordance with the theory from Milgrom and Weber [16].

Vogt and Xu [23] uses both OLS regressions and the order statistics approach (taken from Song, Adams, and Athey and Haile) to estimate demand for digital cameras on eBay. Vogt and Xu argue that these methods for estimating demand are superior to the traditional method, which usually relies on examining exogenous changes in supply and price (such as an item going on sale) to determine the value distribution. Like Adams [1], the results of the OLS regression overestimate the demand for items. Tangentially, they also find that digital cameras have large substitute effects, with high prices on one type of camera often leading people to buy other cameras from the same maker (but not from other brands).

Similar to the research on optimal behavior for sellers, analysis was being performed for optimal behavior for buyers. Milgrom and Weber [15] derives a model for how bidders should bid in a series of auctions for identical items, such as the RCA spectrum auctions, in which every bidder only wishes to win one item. They find that, for a series of English auctions, in equilibrium every
item will sell for the same price, which is identical to the equilibrium if the auctions were run simultane-ously. They characterize optimal bidding strategy and show that, in equilibrium, the price should be equal to the value of the N + 1 highest bidder. In first price and second price auctions, however, the series of prices is expected to be upward drifting.

Zeithammer [24] extends Milgrom and Weber [15] with a model for optimal bidding in which multiple homogenous items of the same type are listed both simultaneously and sequentially with an infinite time horizon — in other words, in the way they are listed on eBay. The idea is that if a bidder wants just one of a homogenous good, like a DVD, they might be willing to make a tradeoff between winning an item now and winning an item later for less. Zeithammer tests three different models of bidder behavior, one with no forward looking, one with moderate forward looking (auctions that will end within a few hours), and one with significant forward looking (auctions that will end within a few days). An empirical test on DVDs and mp3 players revealed that the best explanation for the bidding behavior is the most forward looking model, suggesting that bidders bid optimally in eBay auctions.

There has also been some recent work done on posted price mechanisms. eBay offers sellers the option to have a Buy-It-Now price, which a bidder can at any time pay to immediately end an auction. Durham, Roelofs and Standifird [6] observed auctions with and without Buy-It-Now prices and ran their own controlled experiments, and they found that sellers with high reputations sell more often via Buy-It-Now and that buyers exercise the Buy-It-Now option more often when the price is lower. Golde [8] analyzed how market thickness affected seller’s pricing decisions for the posted price selling mechanism from Gaia Online. He found that sellers are forward looking, pricing according to expected market conditions and not market conditions at the time of listing.

In conclusion, significant research has been done to characterize optimal bidding and selling behavior in auctions, specifically for eBay auctions. Most papers conclude that bidding and selling behavior on eBay conforms well to theoretically optimal behavior.
3 World of Warcraft

World of Warcraft is a massive multiplayer online role playing game (MMORPG). It takes place in a perpetual, online world where thousands of players come together to play with and against each other. The game currently has over 10 million active subscribers, each of whom plays on one of the game’s several hundred servers. Each server, in turn, hosts a version of the world estimated to be equivalent to hundreds of square miles [21].

While playing the game players can earn, find or buy items. There are some thirty thousand unique items in World of Warcraft [20] that fall into several major categories, of which we shall focus on two: trade goods like cloth, leather and metal, and durable goods, like weapons and armor.

Almost all items can be traded in an in-game auction house that can be accessed from any major city. Players who list items can specify the minimum bidding price as well as, if they wish, a buyout price. This buyout price is equivalent to Buy-It-Now on eBay; unlike on eBay, however, when someone places a bid the buyout price remains, and so it can always be exercised. They can also specify the length of the auction, choosing from twelve, twenty-four or forty-eight hours. For any item in the game except trade goods there is a cost to listing an item, and listing an item for longer costs more. Some items, notably trade goods, can be sold in stacks, usually of up to twenty items.

Players who search for items can search and sort by any number of characteristics, including name, count, quality, level, minimum bid, bid amount, buyout price, and owner. Players can then either bid on items or, if the option is available, buy the item immediately for a specified buyout price. When a player bids, there is a minimum increment determined by the game, and they can bid any amount over the current price plus the minimum increment. When a bidder places a bid, the money for the bid is immediately removed from their account, though it is returned when they are outbid.

In browsing goods, a player cannot see how many minutes remain in the auction; instead, they
see a number between one and four. One means fewer than thirty minutes, two means between thirty minutes and two hours, three means between two and twelve hours, and four means between twelve and forty-eight hours.

For a more detailed description of the game, see Appendix A.

4 The Data

For details on how the data was gathered, including potential flaws in the data, see Appendix B.

4.1 Auction Data

The auction data consists of 446,880 auctions occurring over 19 days in January and February of 2009. The data was all gathered from one server, Maelstrom, which is located in the United States. The data was all gathered from the Auction House belonging to the Hoard faction. The data set contains 21,319 unique items, which were listed by 8,077 unique owners.

There are also a variable number of auctions available on the auction house at any particular time. The minimum number of auctions observed was 17,166 on Tuesday, February 10th at 10:50PM, and the maximum number of auctions observed was 24,491 on Saturday, January 31st at 1:19PM. Figure 1 shows the number of auctions during the sample time. Note that all outages except the Tuesday update\(^1\) were due to the script stopping scanning for more than an hour and so the market operated unobserved during these periods. During the Tuesday update, however, no one was able to access the auction house, and so no players were able to list new auctions.

4.2 Census Data

The census data consists of 31,466 observations occurring over 25 days in January and February of 2009. Of these 8,098 (about 25\%) occurred within a minute of the previous observation and

\(^1\)See Appendix B for details on outages during data collection.
26,672 (about 85%) occurred within two minutes. No two observations during regular operation occurred more than five minutes apart.

5 The Market

5.1 Items

Of the 446,880 observed auctions 63% were sold and 37% expired. Of those that sold 97% were sold via buyout and only 3% through bidding. Of the 21,319 unique items, 8,445 (about 40%) were only observed once, 17,798 (about 83%) were observed fewer than 10 times, and only 729 (about 3.5%) were observed more than 100 times. The most observed item, Saronite Ore, was observed 9,004 times. The mean number of observations is 20.96 and the median number of observations is 2. Figure 2 shows what percentage of observed auctions were of what percentage
of the observed items. The figure shows that the market primarily consists of a small number of highly auctioned items and a large number of infrequently auctioned items. Note that the same pattern is not generally true of eBay, which has a much more even distribution of item types [7].

![Figure 2: Market Makeup — Items](image)

### 5.2 Prices

A similar pattern is observed for the sale prices of items, namely that a large percent of the auctions sell for a small price and a very small percentage of the items make up the vast majority of the price distribution. Figure 3 shows what percentage of the price distribution represents what percentage of the observed auctions.
5.3 Owners

Of the 8,077 unique owners 802 (about 10%) were only observed once, 3,242 (about 40%) were observed fewer than 10 times, and only 966 (about 12%) were observed more than 100 times. The most observed owner, Earfwinfyre, was observed 4,115 times. The mean number of observations is 54.9 and the median number of observations is 15. Figure 4 shows what percentage of the market is due to what percentage of the observed owners. The plot includes both percent of total listings and percent of total revenue. The figure shows that the market has a wide variety of participants. A small percentage of players do control a sizable portion of the market, and a modest percent of players are largely absent from the market, but there is a smooth middle section in which players have market experience but not market power.
5.4 Bidders

Since users can only bid on items when they are in a major city, the number of potential bidders can be approximated by the number of people in a faction’s major cities. We see that the number of potential bidders is strongly affected by the hour of the day, as seen in Figure 5. The dotted lines represent one standard deviation in either direction.

All times are in PST, so the peak occurs at 4pm PST and 7pm EST. There is also variation between days, but the maximum number of users remains rather constant, as seen in Figure 6.

We also see in Figure 7, however, that though the maximum number of users on a week day verse a weekend is roughly similar, users start playing much earlier on the weekend and spend more of the day playing.
6 Behavior

One of the questions that comes to mind with data from World of Warcraft is that players are dealing with a virtual currency that they may or may not treat in the same way as real world currency. That is to say that the usefulness of World of Warcraft as a testing ground for economic ideas could be jeopardized if people think that results from World of Warcraft do not apply in the real world. Before this can be tested, however, we must first state how we expect bidders and sellers to behave in this market.

6.1 Bidders

For almost all players there exist durable items such as weapons or armor on the auction house that are superior to those they are currently using. A player has the choice of whether to attempt to upgrade their gear through fighting monsters or whether to attempt to upgrade their gear through
Figure 6: Bidders — Within Day
purchases from the auction house. If a user decides to purchase an improvement, we assume that they have a unit demand for goods of that type. We also assume that they evaluate items solely based off their performance and not their appearance. This latter assumption is reasonable because, though some items do have aesthetic value, especially at lower levels weapons and armor are quickly discarded as a player rises through the ranks, and so it makes little sense to make a purchase for aesthetic purposes.

For consumable goods (trade goods), however, we assume that a player not only demands more than one unit of the good at a time, but that they demand the good over time. Sometimes a player will wish to purchase trade goods in the anticipation of requiring them later and will thus be highly price elastic, but other times a player will require a fixed number of units of the trade good and will thus be highly price inelastic. In both cases we assume that whenever a player decides to purchase a good, that they will always purchase the cheapest available auction for that good.
Because the auction house has ascending first price auctions, if a player wants to buy an item through the bidding mechanism, their approximately optimal strategy is to bid the minimum amount and then to monitor the auction, constantly bidding the minimum increment above each opposing bid until either they win the item or the listing price exceeds their value. Note, however, that such a process is incredibly onerous and thus, as described in more detail in Section 8.2, almost every auction is sold via buyout. Note as well that this strategy is only approximately optimal because there may be multiple equilibria involving using jump-bidding to signal value. See Section 7.5 for an analysis of jump bidding.

6.2 Sellers

We assume that a seller’s preferences include three things: expected revenue, probability of sale, and time to sale. Sellers have diverse preferences with respect to the relative importance of these factors. We also assume that a player will have only one unit of any trade good but multiple units of any trade good they wish to sell.

7 Rationality

We now devise several tests to argue that not only is the currency being valued, but it is being valued consistently.

7.1 Probability of Sale

While most items are sold infrequently, there are a handful of items that are auctioned extremely often. As Figure 2 shows, 20% of the items account for perhaps 90% of the auctions. Almost all of these frequently auctions items are trade goods. The type of people who demand these items are incredibly diverse — everyone from low level players attempting to craft items for their own use to high level players trying to learn a new trade skill.
Because multiple instances of these goods are auctioned at one time and because they are auctioned over time, players end up facing tradeoffs between price and impatience. If people truly had no value for World of Warcraft currency, then whenever they decided to buy a certain kind of good they would purchase whichever auction showed up first in their search. If they valued the currency, however, we would then expect auctions with higher prices to sell less frequently.

To examine this the data set was restricted to only auctions of the fifty most common items, which lowered the number of observations from 446,880 to 63,353 auctions, and only in the most common stack size, which lowered the number of observations to 51,188 auctions. Because these auctions sell for very different prices, a Z score was calculated for every item that used the mean and standard deviation of the price of all items of that type that sold via buyout within each day. Finally, the probability of sale was calculated for each Z score. See Figure 8 for the results.

![Figure 8: Probability of Sale — Top 50 Items](image)

Note that the data set contains several outliers with very high Z scores that were excluded from
the plot for scaling reasons. None of these auctions sold, however, and so the results remain the same.

This plot at the very least shows that players value these goods and the World of Warcraft currency in a fundamental way. Just as one would expect an item listed for a low price sells with a high probability, and an item listed for a high price sells with a lower probability. Furthermore, while auctions at the mean listing price sell with the high probability of 93%, the probability of sale begins to quickly diminish: only 77% of auctions sell with a Z of 1.0, and only 22% sell with a Z of 3.0.

### 7.2 Time to Sale

Another way to confirm that there is some sort of value distribution for these goods is to look at how long it takes an item to sell. If people simply bought the first item that they saw then there should be no observable relationship between the listing price and the time to sale. If, however, each bidder has a value for each good, and they buy an item if their value exceeds the purchase price, we would expect to see an upward sloping trend between the two.

The data set used to examine this is identical to the data set in the previous subsection, with Z scores used to normalize between items. See Figure 9 for the results.

Note that there are Z scores beyond the shown range. Those with lower Z scores all sold in a similarly short amount of time, but those with higher Z scores had more variation both because there are very few auctions with Z scores that high and because almost all of the auctions with scores that high didn’t sell at all. Thus the plot was restricted to items that sold with a probability of about 0.10 or higher.

This plot shows a clear upwardly sloping trend between listing price and time to sale. The good deals are quickly observed and purchased while the more highly priced items, if they sell at all, remain for a long time before a player comes along with a high enough value, large enough demand, and a sufficient amount of impatience to purchase all goods of lesser or equal price.
7.3 List Prices

The last two subsections examined the manner in which bidders responded to items on the auction house. We now turn for a moment to a seller’s decision. If we assume that price, probability of sale, and time to sale are incorporated in a player’s utility function, then because we have shown that buyers react in predictable ways to price dispersion, a seller faces their own tradeoffs in choosing for what price to list an item. Undoubtedly some sellers will wish to sell a good instantly and so post it for a low price, and some sellers are willing to wait longer for higher returns.

To examine this we use the same data set as in the previous two sections. See Figure 10 and Figure 11 for the results.

These plots suggest that people are doing a good job of evaluating and responding to their tradeoffs. There are indeed people who want to sell items quickly and with high probability, but there are very few who sell for so low that they leave a lot of money on the table. In fact, only
Figure 10: Listing Distribution — Top 50 Items

Figure 11: Listing Distribution — Top 50 Items
4.1% of auctions could be listed for a higher price without decreasing the probability of sale, and on average these auctions only left 10% of their expected revenue on the table. Additionally there are indeed people who want to sell items for higher prices, but there are very few who sell for so high that there is no chance of a sale. In fact, fewer than 1% of listings have a zero percent probability of sale. This is especially remarkable seeing as players can only see currently listed auctions, so they should have no idea of what the probabilities of sale and time to sale are for any particular item.

### 7.4 Expected Revenue

There are only three real variables in the selling of an auction: the expected revenue, the probability of sale, and the time to sale. We thus assume that these are all incorporated into a seller’s utility function. We now briefly examine a proxy for expected revenue to see what decisions sellers are making, and if these decisions make sense.

What we would expect to see is that the mean of the listing price distribution is less than the price that would give the maximum expected revenues. This is because expected revenues should be parabolically shaped, and so anyone listing above the maximum point of that parabola could receive the same expected revenues but with a higher probability of selling and a faster time to sale by listing at the price that is opposite their price on the parabola. Additionally, a seller would only list at the maximum revenue point if they did not care about the probability of sale, which anatomically factors heavily into a seller’s preferences. There is such a high cost to listing items (not in gold but in the time required to get to the auction house) that sellers most likely care quite a bit about probability of sale.

To examine this issue we use the same data set as the previous three sections. This does present a problem in that the best we can calculate is what listing Z value maximizes the expected Z, which captures the spirit of expected revenue but has some issues. The main issue is the fact that a negative Z value has a negative expected Z return, while a Z that has a probability of sale of 0
has an expected Z return of 0, which is higher. We thus plot from a Z of 0, because empirically we see that negative Z values do not maximize expected Z. See Figure 12 for the results. Note that the plot becomes erratic to the right of Z of 2 because each point represents significantly fewer observations, and so the sample mean for each point above Z of 2 can lie relatively far from the true mean, which we assume lies on a parabola.

![Figure 12: Expected Revenue — Top 50 Items](image)

This plot too is exactly what we would expect. The average seller could increase their prices to increase their expected revenues, but they choose not to because they care so much about the probability of sale and time to sale that they would rather trade a little expected revenue to improve those.
7.5 Jump Bidding

Thus far all of our arguments have been rather weak. That is to say that we’ve argued that people do indeed value World of Warcraft items and currency. We’ve also argued that buyers appear to be making tradeoffs between impatience and cost, and sellers appear to be making tradeoffs between expected revenue, probability of sale, and time to sale. We now make a slightly stronger argument by claiming that buyers appear to be behaving rationally in their bidding decisions. To do this we look at jump bidding, which is when a bidder places a bid that is for more than the minimum increment. Though items are rarely sold for a bid, our data set does contain 13,212 bidding events, of which 859 (about 6.5%) are jump bids.

The reason a player would want to jump bid is if they wanted to win an auction via bidding (items sold via bidding do so at a significant discount to the mean price, see Section 8.2 for more details) but wanted to diminish the chance that they would be outbid. One manifestation of this might be a player attempting to signal to a competing bidder that they themselves have a high value for an item. For example, if two players are bidding back and forth, one player might decide to jump bid in an attempt to discourage the other player from perpetuating the bidding war. Another manifestation might be a player attempting to decrease the probability of another player discovering the auction and then deciding to bid on it. For example, if an item that usually sells via buyout for 4g has a minimum bid of 1g, a player might not want to bid the minimum amount because it would still be such a good deal that another player might want to risk themselves being outbid to bid on the item. If the original player bids 3g, however, the risk to potential bidders of being outbid might not be worth the extra 1g to buy a the same item with a buyout, so the original bidder could still win the item at a discount from the standard buyout price.

We would thus expect a bidder to jump bid more often when there is a higher chance of someone outbidding them. There are three notable factors that go into the likelihood of them being outbid. The first is how long the auction has left: the longer the auction has left, the higher the probability of someone else bidding on it. The second is how many other people are available to
bid: the more people evaluating an auction, the higher the probability of someone else bidding on it. And finally, there is how long they will be logged out of the game: if they are unable to respond to being outbid, there is a higher probability of them losing the item. To examine how users jump bid the data set of bids was used, and then the indicator variable for a jump bid being present was regressed using the following functional form:\(^2\):

\[
Pr(jumpbid_i = 1 \mid I_i, timeleft_i, hour_i, ..., hour^4_i, week_i, ..., week^4_i) = F(\alpha + \beta_{timeleft} I_i, timeleft_i + \gamma_1 hour_i + ... + \gamma_4 hour^4_i + \delta_1 week_i + ... + \delta_4 week^4_i + \epsilon_i)
\]

See Table 1 for the results. The results are largely in line with what we would expect. When there is a time left of 1, which means fewer than 30 minutes remain in the auction, bidders are unlikely to jump bid because there is very little time in which they could be outbid. When there is a time left of 3, which 12-24 hours remaining, users are about 2.3% more likely to jump bid than if there were a time left of 4, which is 24-48 hours remaining. This makes sense because if there is a time left of 4 it is both likely that they will be back to the auction house before the auction expires, and there is just so much time left that the chance of being outbid might be high regardless of their bid. Finally, the time when users are most likely to jump bid is for a time left of 2, which makes sense because the auction still has 2-12 hours remaining, which is not a short enough period of time to guarantee that a bid would stand but not so long a period of time that they would return to the auction house before expiration.

As a reality check a plot is included of the predicted jump bid probabilities from a regression of jump bid against hour. See Figure 13 for these results. This plot too makes sense because the times in which people are most likely to jump bid are in the middle of the day when the auction will be expiring during peak play time, or late at night when they are about to sign off and therefore cannot defend their bid until they login again the next day.

\(^2\)Note this is a logit regression
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) jumpbid</th>
<th>(2) jumpbid</th>
<th>(3) jumpbid</th>
</tr>
</thead>
<tbody>
<tr>
<td>$time_{left} = 1$</td>
<td>0.486** (0.196)</td>
<td>0.445** (0.198)</td>
<td></td>
</tr>
<tr>
<td>$time_{left} = 2$</td>
<td>0.875*** (0.129)</td>
<td>0.872*** (0.130)</td>
<td></td>
</tr>
<tr>
<td>$time_{left} = 3$</td>
<td>0.378*** (0.0813)</td>
<td>0.400*** (0.0829)</td>
<td></td>
</tr>
<tr>
<td>hour</td>
<td>-0.262*** (0.0989)</td>
<td>-0.223** (0.0997)</td>
<td></td>
</tr>
<tr>
<td>hour$^2$</td>
<td>0.0564*** (0.0176)</td>
<td>0.0471*** (0.0177)</td>
<td></td>
</tr>
<tr>
<td>hour$^3$</td>
<td>-0.00371*** (0.00112)</td>
<td>-0.00308*** (0.00113)</td>
<td></td>
</tr>
<tr>
<td>hour$^4$</td>
<td>7.73e-05*** (2.34e-05)</td>
<td>6.43e-05*** (2.35e-05)</td>
<td></td>
</tr>
<tr>
<td>week</td>
<td>-2.490*** (0.819)</td>
<td>-3.152*** (0.826)</td>
<td></td>
</tr>
<tr>
<td>week$^2$</td>
<td>1.279*** (0.398)</td>
<td>1.577*** (0.400)</td>
<td></td>
</tr>
<tr>
<td>week$^3$</td>
<td>-0.237*** (0.0753)</td>
<td>-0.289*** (0.0757)</td>
<td></td>
</tr>
<tr>
<td>week$^4$</td>
<td>0.0143*** (0.00483)</td>
<td>0.0175*** (0.00485)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.834*** (0.0455)</td>
<td>-1.341** (0.543)</td>
<td>-1.067** (0.544)</td>
</tr>
<tr>
<td>Observations</td>
<td>13212</td>
<td>13212</td>
<td>13212</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Thus we see that on the whole bidders behave how we would expect with respect to jump bidding, which is reason to believe that they are rationally and correctly evaluating their bidding decisions.

7.6 Hedonic Pricing

Finally, we aim to conclude this section with a strong claim that bidders not only value goods and make their decisions rationally, but that they are making them intelligently and consistently. As a note, the smoothness of the results we’ve seen thus far would actually suggest that people are making consistent decisions. For example, bidders treat an auction with a Z of 0.1 only marginally differently than a Z of 0.0 or 0.2, which would suggest consistency in their evaluation.

We now aim, however, to make a stronger claim than that by investigating the prices within an item category, namely weapons, in the auction house. Unlike the items previously examined, there
are very few observed auctions for any particular kind of weapon. For example, of the 420 different
varieties of daggers observed in the data set, 145 of those (about 35%) were only observed a single
time, and 411 (about 98%) were observed fewer than 10 times. Thus the price for most of these
items cannot be based on current listing prices for other copies of the same item. Furthermore,
players not only face tradeoffs between different kinds of weapons, but even if they know that they
want to buy a specific kind of weapon, like a dagger, they face tradeoffs between different varieties
of that weapon. At the most basic level we would expect more powerful daggers to cost more
as players make a money-quality tradeoff. Beyond that, however, one dagger might deal slightly
less damage per second (DPS) but have slightly better stat bonuses, so players are making those
tradeoffs as well. Weapons also, especially at higher levels, have special abilities and bonuses.

One way to examine how players deal with these tradeoffs is to look at the hedonic pricing of
daggers. The choice to examine a weapon is due to the assumption that players evaluate weapons
solely based on how they perform in battle rather than on looks, and thus there are few unobserved
characteristics that effect price. The process of evaluating a weapon before purchase is relatively
straightforward both because all items of the same type are perfectly homogenous and because
all information about how an item assists in battle is public knowledge: to learn all of an item’s
characteristics the user simply has to mouse over it. Even the aesthetics can be quickly examined
by control-clicking on an item, which displays to the user how they would look while wielding
it. The specific choice to examine a dagger is due to the fact that only a single class uses them,
namely Rogues.

Thus because daggers are used by relatively homogenous agents and because these agents are
easily able to value them, we would expect pricing to be consistent across different dagger varities.
To test this claim the data set was restricted to sold daggers. There were 1,938 observed auctions
for daggers in the data set, of which only 788 were sold.
The following functional form was used for the regression:

\[ p_i = \alpha + \beta_1 D_{i,\text{DPS}} + \ldots + \beta_5 D_{i,\text{DPS}}^5 + \gamma_1 \text{stamina}_i + \ldots + \gamma_3 \text{stamina}_i^3 + \delta_{i,\text{quality}} D_{i,\text{quality}} + \epsilon_i \]

Since a Rogue’s role in battle is to inflict damage, DPS should be the primary source of differences in value. The next terms are from the bonus to stamina, which increases the effectiveness of the Rogue’s combat moves. Originally the functional form contained both Stamina and Agility, but in no regression were the coefficients on Agility statistically significant, so they were dropped. Anecdotally the author had heard that both were valuable to a Rogue, but buyers proved unwilling to pay for Agility bonuses. The final terms are indicator variables for the four tiers of quality. Many weapons have special abilities, such as an increase in attack power, a chance of extra damage on hit, etc. Though these special abilities are all unique, the quality of this bonus is largely captured in the quality of the item. The results of the regression appear in Table 2.

Almost every coefficient in the three regressions is statistically significant at the 1% level, and the final \( R^2 \) is up to 0.992. This means that essentially all variation in the prices of daggers can be explained solely from their characteristics. This is thus strong evidence to the claim that users are pricing items consistently, as we would expect from rational agents. This is especially remarkable considering that most of the daggers were purchased a time when they were the only dagger of that variety on the auction house, and so the price had to be determined by rational comparisons with other available daggers. These comparisons were made incredibly consistently.

8 Differences with eBay

The original intention of this paper was to perform analysis on World of Warcraft auction data identical to what has been performed on eBay auction data. The hope was that results from eBay could be confirmed on Warcraft data, which would suggest that players treat in game currency
Table 2: Estimation Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) saleprice</th>
<th>(2) saleprice</th>
<th>(3) saleprice</th>
</tr>
</thead>
<tbody>
<tr>
<td>$dps$</td>
<td>182222***</td>
<td>58755***</td>
<td>28754***</td>
</tr>
<tr>
<td></td>
<td>(14361)</td>
<td>(10647)</td>
<td>(4043)</td>
</tr>
<tr>
<td>$dps^2$</td>
<td>-9033***</td>
<td>-2608***</td>
<td>-1842***</td>
</tr>
<tr>
<td></td>
<td>(609.7)</td>
<td>(477.5)</td>
<td>(180.2)</td>
</tr>
<tr>
<td>$dps^3$</td>
<td>188.9***</td>
<td>54.96***</td>
<td>48.45***</td>
</tr>
<tr>
<td></td>
<td>(10.81)</td>
<td>(8.928)</td>
<td>(3.366)</td>
</tr>
<tr>
<td>$dps^4$</td>
<td>-1.703***</td>
<td>-0.532***</td>
<td>-0.515***</td>
</tr>
<tr>
<td></td>
<td>(0.0842)</td>
<td>(0.0725)</td>
<td>(0.0274)</td>
</tr>
<tr>
<td>$dps^5$</td>
<td>0.00548***</td>
<td>0.00191***</td>
<td>0.00189***</td>
</tr>
<tr>
<td></td>
<td>(0.000238)</td>
<td>(0.000210)</td>
<td>(7.98e-05)</td>
</tr>
<tr>
<td>$stamina$</td>
<td>224074***</td>
<td>114739***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13471)</td>
<td>(5569)</td>
<td></td>
</tr>
<tr>
<td>$stamina^2$</td>
<td>-22012***</td>
<td>-13145***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1010)</td>
<td>(408.6)</td>
<td></td>
</tr>
<tr>
<td>$stamina^3$</td>
<td>424.7***</td>
<td>281.6***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16.50)</td>
<td>(6.597)</td>
<td></td>
</tr>
<tr>
<td>$quality = 2$</td>
<td>40025</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(50493)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$quality = 3$</td>
<td>495585***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(52171)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$quality = 4$</td>
<td>1.779e+06***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(58028)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-997751***</td>
<td>-330411***</td>
<td>-164600***</td>
</tr>
<tr>
<td></td>
<td>(99426)</td>
<td>(70349)</td>
<td>(52298)</td>
</tr>
</tbody>
</table>

Observations: 788, 788, 788
$R^2$: 0.866, 0.943, 0.992

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
identically to real currency. Unfortunately the auction mechanism in World of Warcraft differs in a few important ways from that used in eBay, and these differences render useless the techniques employed to analyze eBay data. Two such differences and their impacts are described below.

### 8.1 The Value of Experience

It is common practice on eBay for the buyer to send their money before the seller ships the purchased item. Because of this there is a worry amongst buyers that a seller will not ship a purchased item, and indeed the buyer has little recourse if this does happen. To mitigate this worry eBay introduced a feedback system by which a buyer can rate a seller when a transaction has been completed successfully. Houser and Wooders [11] finds that bidders are willing to pay a large premium for bidders without negative feedback and a smaller but still significant premium for those with positive feedback. Lucking-Reiley [14] finds similar results. Durham, Roelofs and Standifird [6] performed a controlled experiment with eBay auctions and were surprised to find that their auctions were purchased significantly less often than identical auctions from other sellers. They attribute this difference to the fact that their experimental eBay account had no feedback ratings.

World of Warcraft, however, has none of these worries. When someone places a bid for an item the money to cover the bid is immediately removed from their account, and when an auction expires that money is instantly delivered to the seller and the item is instantly delivered to the buyer. Thus there is absolutely no risk in these transactions. The precise experience of a seller is also largely unobservable, as the only data a player receives is the name of the player who listed any particular auction. The most experienced sellers, however, will stand out because they will represent a sizable proportion of the auctions of a particular item at any given time. We now investigate how bidders react to auctions from a top seller. It is possible that, conditional on price and time of listing, a top seller’s auctions will be bought less often because players are unhappy that they have market power. Alternatively, players might only care about price, in which case a top seller will sell with equal probability.
There were two ways in which this was tested. The first was to use the same Z score data set from previous sections but to restrict it to top sellers, defined to be the smallest collection of people who together listed 25% of the observed auctions, and bottom sellers, defined to be the largest collection of people who together listed 25% of the observed auctions. There were 12 top sellers and 2,251 bottom sellers, which means that there is a collection of 12 people that together listed the same number of auctions as a different collection of 2,251 people. All other owners were then dropped from the data set. The following functional form was then used for a regression:

\[
sale_i = \alpha + \beta \text{topseller}_{i,j} + \gamma_1 Z_i + \gamma_2 Z_i^2 + \gamma_3 Z_i^3 + \epsilon_i
\]

See Table 3 for the results.

As we see our regression determines that a top seller has on average an 8.6% less chance of selling an item, conditional on price, than a bottom seller. This number was calculated by averaging the coefficients for each of the twelve top sellers. We now attempt to determine whether there are unobserved differences between the auctions listed by top and bottom sellers that would account for the lower probability of sale. There are three things that come to mind: a top seller might list more often during the week and thus sell less often; a top seller might list more often in off hours and thus sell less often; and a top seller might list large groups of items at a time and thus sell less often.

The first two of these were tested by restricting the data set to be only auctions of the most common item (Saronite Ore), only of the most common stack size (20), and with only sellers in the top and bottom twenty-five percent in terms of number of listings. These were made up of 2 and 142 sellers respectively. The following functional form was then used:

\[
sold_i = \alpha + \beta \text{topseller}_{i,j} + \gamma_1 \text{price}_i + \ldots + \gamma_3 \text{price}_i^3 + D_{i,\text{hour}} + E_{i,\text{wday}} + F_{i,\text{hour}\times\text{wday}} + \epsilon_i
\]
Table 3: Estimation Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Seller 1</td>
<td>-0.00150</td>
</tr>
<tr>
<td>Top Seller 2</td>
<td>-0.0633***</td>
</tr>
<tr>
<td>Top Seller 3</td>
<td>-0.140***</td>
</tr>
<tr>
<td>Top Seller 4</td>
<td>0.00837</td>
</tr>
<tr>
<td>Top Seller 5</td>
<td>-0.168***</td>
</tr>
<tr>
<td>Top Seller 6</td>
<td>-0.0602***</td>
</tr>
<tr>
<td>Top Seller 7</td>
<td>-0.0626***</td>
</tr>
<tr>
<td>Top Seller 8</td>
<td>-0.0811***</td>
</tr>
<tr>
<td>Top Seller 9</td>
<td>-0.0523***</td>
</tr>
<tr>
<td>Top Seller 10</td>
<td>-0.344***</td>
</tr>
<tr>
<td>Top Seller 11</td>
<td>0.0438***</td>
</tr>
<tr>
<td>Top Seller 12</td>
<td>-0.110***</td>
</tr>
<tr>
<td>Z</td>
<td>-0.104***</td>
</tr>
<tr>
<td>Z^2</td>
<td>-0.0291***</td>
</tr>
<tr>
<td>Z^3</td>
<td>0.00331***</td>
</tr>
<tr>
<td>Constant</td>
<td>0.966***</td>
</tr>
<tr>
<td>Observations</td>
<td>25453</td>
</tr>
<tr>
<td>R^2</td>
<td>0.317</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1
See Table 4 for the results.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) sold</th>
<th>(2) sold</th>
<th>(3) sold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Seller 1</td>
<td>-0.0802***</td>
<td>-0.0666***</td>
<td>-0.00223</td>
</tr>
<tr>
<td></td>
<td>(0.0128)</td>
<td>(0.0135)</td>
<td>(0.0152)</td>
</tr>
<tr>
<td>Top Seller 2</td>
<td>-0.00943</td>
<td>0.0101</td>
<td>-0.0116</td>
</tr>
<tr>
<td></td>
<td>(0.0142)</td>
<td>(0.0143)</td>
<td>(0.0154)</td>
</tr>
<tr>
<td>price</td>
<td>2.25e-06</td>
<td>1.57e-05***</td>
<td>2.96e-05***</td>
</tr>
<tr>
<td></td>
<td>(5.92e-06)</td>
<td>(5.93e-06)</td>
<td>(7.04e-06)</td>
</tr>
<tr>
<td>price^2</td>
<td>-1.34e-11</td>
<td>-5.88e-11***</td>
<td>-1.08e-10***</td>
</tr>
<tr>
<td></td>
<td>(2.24e-11)</td>
<td>(2.23e-11)</td>
<td>(2.60e-11)</td>
</tr>
<tr>
<td>price^3</td>
<td>7.57e-18</td>
<td>5.29e-17**</td>
<td>1.07e-16***</td>
</tr>
<tr>
<td></td>
<td>(2.74e-17)</td>
<td>(2.68e-17)</td>
<td>(3.03e-17)</td>
</tr>
<tr>
<td>Hour Dummies (23)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Day Dummies (6)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hour Day Interaction Dummies (138)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>0.966*</td>
<td>-0.235</td>
<td>-1.336**</td>
</tr>
<tr>
<td></td>
<td>(0.504)</td>
<td>(0.505)</td>
<td>(0.609)</td>
</tr>
<tr>
<td>Observations</td>
<td>3522</td>
<td>3522</td>
<td>3522</td>
</tr>
<tr>
<td>R^2</td>
<td>0.052</td>
<td>0.190</td>
<td>0.428</td>
</tr>
<tr>
<td>Adj R^2</td>
<td>0.050</td>
<td>0.182</td>
<td>0.402</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We see that the first regression, though it is on a different data set, has a similar coefficient on the first top seller to our previous result. By the third regression, however, the coefficient on both has shrunk and is no longer statistically significant. Thus there does not appear to be any significant effect on the probability of sale from being a top seller verse a bottom seller.
8.2 Buy-It-Now

Durham, Roelofs and Standifird [6] find that on eBay only experienced sellers choose to have a Buy-It-Now price, and on the whole only about 33% of eBay auctions include a buyout price. This is because the optimal buyout price is in practice difficult to calculate because it requires an estimation of the value distribution from data, and so it is likely that a seller would have higher expected revenues by letting the auction mechanism work on its own. As Vickrey [22] showed, in a second-price auction the buyer’s optimum strategy is to bid their value, and because eBay employs a proxy bidder, the mechanism almost replicates a second-price auction. Thus the auction without a buyout price (but with a reserve price) should approximate a revenue maximizing auction.

World of Warcraft, by contrast, does not employ a proxy bidder, so the bidder must pay exactly what they bid. Many auctions in the real world are similar, but most of these are physical auctions where the bidders sit in a room and bid up the item until a winner has been determined. World of Warcraft, by sharp contrast, has the auctions persist for a minimum of 12 and maximum of 48 hours. Thus there is no guarantee that the bidder will be logged into the game when they are outbid. Furthermore, even if they are logged into the game, it is incredibly costly to bid, as it can take upwards of 15 minutes to travel back to the auction house. Reacting to this, players incredibly rarely buy items via the bidding mechanism.

Of the 283,205 observed sold auctions, 274,671 (about 97%) were sold via buyout, while only 8,534 (about 3%) were sold via bidding. Furthermore, of the 446,880 observed auctions, only 4,574 (about 1%) declined to list a buyout price (in contrast to 67% on eBay), whereas 62,134 (about 14%) made the minimum bid the same as the buyout price, which makes the auction a posted price listing. Of the top 50 items, those that listed without a buyout price were also 20% less likely to sell than an item with a buyout price equal to the minimum bid.
9 Why Auction Theory Is Important

We thus see one reason why auction theory is important. In short, the World of Warcraft auction house is supposed to be an auction house, but it’s not. The game’s designers wanted to guarantee that a bidder could cover their bid, and so they decided to remove the money for the bid immediately from their account. This in turn induced them to make the auction house a first-price auction, so no more money than was necessary had to be removed from an account. While in many circumstances this change would be insignificant, in this case the cost of bidding is so high that the players have largely abandoned the auction mechanism. Anyone with a modicum of auction theory knowledge could have foreseen this, and the simple change of adding an eBay-style proxy bidder would have greatly simplified the process of auctioning items. This small aspect of the auction mechanism also is responsible for rendering the data rather incomparable to eBay data, because when an item is sold for a posted price, the selling price is not the item’s value to the second highest bidder.

10 Conclusion

If World of Warcraft were a country, it would have more residents than Belgium, the Czech Republic, or Greece. People study the economies of these countries, but no one yet has studied the economy in World of Warcraft. This is made even more puzzling by the fact that the kind of data available on World of Warcraft is orders of magnitude more extensive and complete than any real world micro or macroeconomic data. A researcher working with the game’s creators could know every movement, every action, and every word spoken by every agent in the entire game. They could know every player’s wealth, characteristics, friends, colleagues, bidding behavior, and listing behavior. Additionally because the game is run on multiple servers with identical conditions, a controlled experiment could be run with a precision and study unparalleled in the real world. The game’s creator’s have precise control over the supply of a given item (through it’s drop rate),
and so the full effects of supply and demand in action could be carefully studied in a complex economy. This is, however, just one possible tactic. A bug in the game that acted like a contagious infection made headlines months ago when researchers realized that World of Warcraft could be used to study the spread of disease. And if the spread of disease could be studied, the prevention of that spread could be studied as well, and in a manner that simulated the real world better than any model ever could.

Put simply, World of Warcraft is an absolutely fantastic testing grounds for economic theories. The only issue is whether or not results from the game have significance in the real world. The first step to answering this question is to look at how users treat the game’s currency. As demonstrated in this paper, there is evidence to support that users do indeed value the currency intelligently and consistently. Further study is certainly necessary, but initial results look promising.
11 Appendix A: World of Warcraft

11.1 World of Warcraft

World of Warcraft is a massive multiplayer online role playing game (MMORPG). It takes place in a perpetual, online world where thousands of players come together to play with and against each other. The game currently has over 10 million active subscribers, each of whom plays on one of the game’s several hundred servers. Each server, in turn, hosts a version of the world estimated to be equivalent to hundreds of square miles [21].

When a player begins the game they choose from ten playable races and nine playable classes. They can also choose two professions, which then allow them to gather special items, usually trade goods like herbs, leather or metal, and then combine them to make other items, such as potions, armor or weapons.

There are several ways a player can advance through the levels, notably fighting monsters, attempting quests, and engaging in player-vs-player (PVP) combat. All three of these provide the player with gold. Additionally, completing a quest or defeating a monster usually yields the player an item or items.

At all levels players are encouraged to work together, and so they can form groups with up to five players. These groups can then tackle dungeons, which contain more powerful monsters that drop similarly more powerful items. At higher levels players can form raid groups with up to forty players. These groups can enter extremely difficult dungeons, from which the game’s most powerful items are obtained.

11.2 The Goods

There are some thirty thousand items in World of Warcraft [20]. Items are initially obtained in a multitude of different ways: some items are dropped by monsters, some are quest rewards, some
are found within chests, some are caught when fishing, some are harvested from the world through mining, herbalism, or skinning, some are made through a profession, some are purchased with gold from Non-Player-Characters (NPCs), and some are purchased with honor points from NPCs. Many items can be obtained through several of these methods, though most of the most powerful items can only be obtained a single way.

The goods are also incredibly diverse. There are ten broad item classes: armor, container, gem, glyph, key, projectile, quiver, recipe, trade good, and weapon. Each of these has several sub-classes. For instance, weapons have the following sub-classes: axe, bow, crossbow, dagger, fishing pole, fist weapon, gun, mace, misc, polearm, staff, sword, thrown and wand. Some items are intended to be used to create other items, such as the trade goods cloth, herbs, leather, and meat. Other goods are intended to just for enjoyment, like a rare fish that makes your character look like a pirate, ornamental clothing like a bandit’s mask, or toys like leather balls that players can throw to each other. There are also items that help during battle, like healing potions of a dozen varieties and levels.

Not all players can use all items. For example, only certain classes can use certain tiers of armor: healers can only wear cloth armor, while warriors can wear all types up to and including plate mail. Certain items can also only be used by certain professions (any gadget crafted by an engineer can only be used by an engineer), certain races, or certain classes.

Players store items either in bags they carry with them or in a bank that can be accessed from any major city. Both means have limited storage capacity, though they can be expanded several times through containers. Items can also be given to other players, either through direct trade or via a mail system. Not all items, however, can be given away. Many of the most powerful items bind on pickup (BOP), which means that once the item has been picked up, the owner cannot give the item to another player. Additionally many items are bind on equip (BOE), which means that players can trade the item to each other, but as soon as someone uses the item (wields a weapon or dons an armor), they can never trade the item again.
All goods of the same type are perfectly homogenous.

11.3 The Auction House

Any item that is not bound to a person can be traded in an in-game auction house. The auction house can be accessed from any of a faction’s major cities, with all auction houses for the same faction being linked. There are also neutral auction houses, located in neutral cities, in which players of different factions can trade items, though these are much less used because players make many fewer visits to neutral cities than to their own faction’s major cities.

Players who list items can specify the minimum bidding price as well as, if they wish, a buyout price. This buyout price is equivalent to Buy-It-Now on eBay; unlike on eBay, however, when someone places a bid the buyout price remains, and so it can always be exercised. They can also specify the length of the auction, choosing from twelve, twenty-four or forty-eight hours. For any item in the game except trade goods there is a cost to listing an item, and listing an item for longer costs more. Some items, notably trade goods, can be stacked in a person’s bag, and for every item there is a maximum stack size, which is usually twenty for a trade good. Someone creating an auction for one of these items can list the item for any permitted stack size.

Players who search for items can search and sort by any number of characteristics, including name, count, quality, level, minimum bid, bid amount, buyout price, and owner. Players can then either bid on items or, if the option is available, buy the item immediately for a specified buyout price. When a player bids, there is a minimum increment determined by the game, and they can bid any amount over the current price plus the minimum increment. When a bidder places a bid, the money for the bid is immediately removed from their account, though it is returned when they are outbid.

In browsing goods, a player cannot see how many minutes remain in the auction; instead, they see a number between one and four. One means fewer than thirty minutes, two means between thirty minutes and two hours, three means between two and twelve hours, and four means between
twelve and forty-eight hours.

12 Appendix B: Gathering The Data

12.1 Gathering Auction Data

The makers of World of Warcraft, Blizzard Entertainment, created a way for players to customize their interaction with the game through scripting and user-interface addons. Blizzard made available to users an API, which has commands to interact with the game. Of particular interest are the commands to interact with the auction house, which include searching the auction house and getting information on specific auctions.

As soon as an auction is bought or expires it is immediately removed from the auction house, so the difficulty in obtaining the data is reconstructing transaction level data from current listings. The reason this distinction is important is that there are a series of common addons to the game that allow the user to scan the auction house, compiling a set of list prices. These then allow players to list their own items more intelligently and note when it might be beneficial to buy an item for resale at a higher price. Because of the prevalence of these addons, however, there are people who purposefully list a set of items for much higher than they usually sell in an attempt to bias these estimates upwards so that they can then list items for higher than they usually sell with the hope that these will appear as good deals on people’s scanners. Because of this, and just for the sake of obtaining more relevant data, it was necessary to construct data on sold items.

The way this was accomplished was through a script that would continuously scan the auction house, reconciling a current image with old images to determine the sequence of bids on items, when items were bought out, when items expired, and for how much they sold.

The API command to search the auction house has an option to obtain an image of the entire auction house. This option, however, is only available once every fifteen minutes, and so the
backbone of the scanning script was to obtain a full image every fifteen minutes and reconcile this with the previous image.

In between those complete scans the script would perform a series of shorter scans in order to augment the last image obtained. One scan performed was a page-by-page scan of auctions with a short time left — that is to say, auctions with less than thirty minutes until expiration. This was done so that the script could determine whether auctions were bought out in the last fifteen minutes or if auctions obtained any additional bids in the last fifteen minutes.

The other scan formed was a page-by-page scan of the first five pages of the auctions with a very long time left — that is to say, auctions with between twenty-four and forty-eight hours to go. This was done so that the script could determine when new auctions were listed with a very-long time left.

Because each of these scans was relatively short, they could be performed approximately every thirty-seconds.

Blizzard Entertainment built several safeguards into the game to prevent users from writing programs to automatically play their characters and thus automatically either gain experience or earn gold. One of these is that users are logged off of the server if their character is idle for fifteen minutes. Another safeguard is that there is no API for interacting with any of the game’s NPCs, specifically the Auctioneer. There is no way from within the game that the script could overcome these, and so a second script, run outside of the game, was created to prevent logoff. The script was an Applescript, which is a programming language for the Mac designed to help users automate certain tasks. A script was created that would check the pixel colors of various parts of the screen in order to determine if the game was launched, if the user was logged in, if the Auction House was open, and if a scan was being performed. If any of these tests failed, the script knew how to log back into the game and re-start the scanning script.

Additionally, as long as the scanning script was running, the logoff prevention script would randomly press a key every two or three minutes, with the delay selected at random. The random-
ness was necessary because World of Warcraft is setup to detect these scripts, and so this was the best way to thwart them.

12.2 Potential Flaws in the Auction Data

There are several potential causes of flaws in the auction data. The first is that it is possible that two or more bids for an item could be placed within fifteen minutes. If the item did not have a short time left (in which case bids would have been noted in the short scan) this would show up in the data as one bid the size of the sum of all bids placed between full scans.

Another potential flaw is in the reconciling process. When reconciling two scans items were matched on every available characteristic. Its possible, however, that two items could be being sold by the same person, listed at the same time and for the same price, in which case they could be potentially matched to each other. Matching these incorrectly, however, would likely not compromise any of the analysis performed.

Another potential flaw is that people who list items have the option, for a price, of canceling an auction. The script is unable to distinguish between a cancelled item and an item that was bought out. To mitigate against this potential source of bias a check was performed whenever an item disappeared in which its price was compared to all other items of that type currently for sale. If there was an identical item available at the same time with a price ten percent or more cheaper than the item that disappeared, the item would marked as cancelled.

A final potential flaw is in the execution of the Applescript to prevent and handle logoff. Despite working well (certainly over 99% of the time), there are many reasons why a logoff could occur even with the script. For instance, Blizzard might have automatically logged off anyone who had been logged in for more than a certain number of hours in the attempt to thwart players with scripts to play their characters. Or the script could potentially not be sufficiently random to fool the game, at which point an automatic logoff would occur. Additionally, the game’s servers do not have 100% uptime. All of these combine with the effect that there were swaths of time in which the

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auction scanning script was not running, and so any activity in that time would be lost. In the two weeks of scanning, however, there were only three outages of an hour or more, and one of them was due to the game being updated. To mitigate against bias introduced by this flaw, in all analysis any auctions spanning an outage were discarded. Since the outages were essentially random, this should introduce no systematic bias into any of the calculations.

12.3 Gathering Auction House Data

Whenever a full scan was performed a record was kept of how many auctions were currently available on the auction house.

12.4 Gathering Potential Bidder Data

Concurrently with the auction house scanning script, another script was running that attempted to estimate the number of potential bidders. A bidder is a potential bidder if they are in a major city, for only such people are able to access the auction house. The script utilized several other API commands that allow users to search for people within a certain region. The scanning command, however, caps the maximum number of people returned at fifty. Thus the census script began by counting the number of people in each of the three major cities. If any returned fifty, the script would ignore that value and perform a series of scans for each of the races within that city. If any of the races returned fifty, that value would be ignored and the script would scan for every pairwise combination of class and race within that city. Because of these potential expansions it can not be determined exactly how often a census figure would be obtained, but on average it was between one and two minutes.
12.5 Gathering Item Data

Blizzard Entertainment makes available a website called WowArmory that contains information on all of the game’s items. This information can be searched for by name, but the address at which an item’s data is stored has a regular format derived from the item’s unique item number. Depending on the browser with which the user is connecting the source of the webpage will be displayed in its native XML format, which is easy to parse for information. A Python script that spoofed a Firefox browser to obtain XML was combined with a brute force approach to scrape for item information, which was then stored in a Stata readable format.
References


