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Unwrapping the Hot-Toy Problem:

An Analysis of Peak Demand and Price Dispersion in the Holiday Market for Zhu Zhu Pets

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Economic Honors Thesis

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1. **Introduction**

In 2005, the Xbox 360, the second generation of Microsoft’s popular game console, hit the shelves at electronic stores across the country. Outside the stores, game buffs lined up to be the first in the door when the Best Buys or Circuit Citys opened. The consoles sold out, and Microsoft was left with thousands of unsatisfied orders. The previous year, a similar event took place during the holiday buying bonanza, but this time it was Sony’s PlayStation 2. Sony said that “[c]onsumer demand for the new console has exceeded our expectations, and we are doing all we can to fulfill the wish list of people who want a new console under their tree this holiday season” (Harford 1). Indeed, the sellout popular toy is a recurring theme during the holiday season. Some of the more famous episodes include the Cabbage Patch Kids craze of 1983, the 1988 Nintendo game cartridge parental panic, Tickle Me Elmo’s spotlight début in 1996, and 1998’s Furby frenzy, where the strange owl-like electronic creature retailed for $35 but was often sold in the secondary market for upwards of $100 (“What is a Furby”). Alexander Tabarrok dubbed this the “hot-toy problem.” He asks, “News accounts often remark on the high prices found in the resale market compared to the shortages at the regular price, so why cannot the manufacturing firm, rather than the resalers, capture the extra profits?” (513). Many answers have been suggested, from the most straightforward argument that shortages create a positive hype effect and generate free publicity, to more complex game theoretic models of seller-induced excess demand and intentional mispricing (Brandenburger 113). Tabarrok himself offers an intriguing double-edged argument. First, he contends that a larger shortage implies a more elastic demand curve, and therefore, the lost profit to the retailer or manufacturer from maintaining the bellow equilibrium price is actually less than what we would think at first glance. Second, he notes that retailers are concerned that if they raise price during the peak demand pre-Christmas
period, customers will return the popular item after the holiday season when price has fallen back down, only to buy it again at the lower price. The first part of Tabarrok’s argument is the main focus of this paper. If we can establish that a large shortage does not necessarily mean that handsome profits are being left untapped, the various theories of the hot-toy problem become more plausible because the opportunity cost of the shortage is smaller (Tabarrok 515).

Supporting Tabarrok’s argument, a more general peak demand theory that does not apply specifically to shortages, is the elasticity theory, which holds that when demand for a specific item increases, consumers will focus less on minimizing travel costs and more on finding the lowest price such that they become more price sensitive and the demand curve more elastic. If this is true, then as demand rises for a hot toy, potentially resulting in a shortage, we would expect the demand curve to also become more elastic, hence, supporting Tabarrok’s argument of elastic demand in the face of demand-induced shortages. Rather than try to provide an answer to the entire hot-toy problem, I will address the elasticity theory and show that we do in fact observe greater price sensitivity during higher demand periods, thus lending credence to Tabarrok’s reasoning, and subsequently confirming many of the hot-toy theories.

My method of testing the elasticity theory is somewhat irregular, the key element being the use of the dispersion of final bid prices as a measurement of consumer price sensitivity. Furthermore, my definition of price dispersion is unconventional in that I am considering the dispersion of prices consumers paid for individual items rather than the prices offered by individual sellers. I use the very popular Zhu Zhu pet hamster Pipsqueak as my tool of observation. The toy faced shortages at many of the major brick and mortar and online toy outlets during the 2009 holiday season and was the most recent iteration of the hot-toy problem. To keep the data collection manageable I focused only on online sales of the Pipsqueaks. I used
movements in completed auction prices on eBay to estimate the direction of movements in consumer willingness to pay, and subsequently the direction of movements in demand. I could then compare changes in the dispersion of completed auction final prices to estimated movements in demand. I used the day-by-day coefficient of variation (standard deviation divided by mean) as an estimator for elasticity under the reasoning that as price sensitivity increases, shoppers’ willingness to search for the lowest priced item should increase; therefore, we should see a smaller spread in the final auction prices since more price sensitive shoppers will more often not bid on an already expensive auction, but instead, search for, find, and bid up auctions with lower highest bids. I was able to compare price dispersion across pre- and post-Christmas data, between higher and lower estimated demand periods, and between weekdays and weekends. I found that price dispersion appears to rise after Christmas, and that in the highest peak demand period, the coefficient of variation is 26.24 percent below the entire sample average. I do not, however, find substantial evidence of a weekend effect on demand. Hence, my results offer evidence supporting the elasticity theory and Tabarrok’s elasticity argument, and conclude that the opportunity cost of the large shortages repeatedly exhibited by the hot-toy problem may in fact be small.

The paper will proceed as follows: Section 2 covers the previous literature, giving a more in-depth description of Tabarrok’s points, and running through a number of the peak-demand and prevailing theories regarding the hot-toy problem. Section 3 gives a thorough discussion of the elasticity theory and its applicability to online retail and eBay. In Section 4, the data, the collection method, and my reasoning for choosing the Zhu Zhu pets as the case study toy are explained. Section 5 presents some descriptive statistics of the data, and Section 6 offers a discussion of the determination of the peak, or most-peak demand period. Section 7 explains
the method of comparing price dispersion across peak and non- or lesser peak periods and describes the results. Section 8 concludes.

2. **Theories of Peak Demand and the Hot-Toy Problem**

Tabarrok challenges the classical notion of a large shortage. The typical determination of a large shortage depends on the difference between quantity demanded, \( Q_D \), and quantity supplied, \( Q_S \)—the larger the difference the greater the shortage. Consider the first graph in Figure 1. Suppose there are two goods, \( a \) and \( b \), with demand curves \( D_a \) and \( D_b \) respectively, each with a fixed short term supply \( Q_S \). At a price of \( P_C \), conventional measures show good \( a \) with a significantly larger shortage than good \( b \). However, Tabarrok asks for which good a shortage would result in greater profit loss. The answer in this case reverses to good \( b \)—consider the second graph in Figure 1. “The loss in profit is smaller the larger the shortage,” says Tabarrok, “because a large shortage is a sign, ceteris paribus, of an elastic demand curve.” Thus, contrary to conventional wisdom, a large shortage implies that a relatively small increase in price would eliminate the shortage but result in a minimal gain in profit to the retailer or manufacturer. Under the elasticity theory, increases in demand increase price elasticity, in other words as the demand shifts out, it also becomes flatter. Picture this: Toy A becomes a fad, overall demand shifts out mainly thanks to the customers who are fairly elastic, the manufacturer raises price slightly and the market clears, leaving it with only slightly more short-term profits and a toy that is no longer the news-making hit of the season. A smart manufacturer may keep price low, foregoing a little short-term profit to enjoy the other benefits of having a sellout product. Thus, if Tabarrak is indeed correct, many of the following proposed answers for the hot-toy problem become more plausible.
Several simple solutions have been presented to answer the question posed by the hot-toy problem. Brandenburg and Nalebuff offer perhaps the simplest answer, contending that a large shortage in a particular product creates hype, or buzz, and free publicity. Taborrok finds this theory unconvincing. “The buzz theory would work better if the shortage occurred before Christmas only to disappear as Santa approached,” says Taborrok, “but that is not what typically happens” (513). Media buzz only helps if it ultimately results in high profits down the road—being out of stock exactly when everyone wants your product does little good. The case could be made, however, that the benefit to the manufacturer from the hype effect might come in the form of high sales continuing long after Christmas. Moreover, if the product was a collectors’ item, like Beanie-Babies, or had complementary products, like games for a Wii, the hype effect might lead to greater purchases of the complementary goods after Christmas. Regardless, this theory is made more convincing if the foregone profit from maintaining the shortage is minimal. A second simple theory, just the reverse of the hype theory, is that an increase in the price would generate bad publicity, hurting a manufacturer’s or retailer’s reputation and sales of other products (Harford 2). However, this requires a somewhat capricious distinction between good press and bad press.

Haddock and McChesney (1994) make a customer loyalty argument that, faced with a supply or demand shock that would temporarily create a shortage at the current price level, a firm may decide to ride out the shortage rather than increase price in the short term, avoiding inducing long standing customers to look for substitutes. The firm’s concern in this case is that by raising their price to the market clearing level, they may induce some otherwise loyal customers to resort to substitutes with which they may build a relationship and not return to the original product or brand once the transitory shock has passed. The challenge for the firm if they
ride out the shortage is to ensure that the scarce good is allocated first to loyal customers. It is
debatable whether this theory can apply to popular toys, since the hot-toy problem strictly
involves new items that require only a one-time purchase. The firm and the customers would not
have built up a relationship, nor would they need to. Instead, Haddock and McChesney’s theory
is more applicable to markets like restaurants in France facing tourist based demand shocks, or
the airline industry overbooking flights, or newspapers running a particularly hot story but
selling for the same price. Nevertheless, if we can determine that a demand-induced shortage
represents only a small loss in profit under Tabarrok’s reasoning, Haddock and McChesney’s
theory gains more validity.

DeGraba (1995) puts together a game theoretic model of buying frenzies and the
rationale for seller-induced excess demand. He considers a good produced by a monopolist for
which consumers do not yet know their personal valuation but do know the true distribution of
valuations. Suppose, the good is produced at zero marginal cost, and there are 100 risk neutral
customers who each demand one unit. Suppose half the customers will value the good at $1.00
and the other half at $0.60. However, in period one, the customers only know the distribution of
valuations and not their own valuations. In period two, they know their valuations. Hence, in
period one, the customers have an expected valuation of $0.80. Now, assume the monopolist
produces only 99 units in period one, and credibly commits to producing no units in period two.
If the monopolist charges a price of $0.79, any consumer who believes that all other consumers
will purchase the item in period one, will also purchase in period one because waiting till period
two would leave him with nothing to buy. Thus, all consumers will purchase in period one,
creating excess demand at a higher price than the profit maximizing price the monopolist would
be able to charge in period two.
DeGraba’s model is a particularly useful way of considering the hot-toy problem since the model requires a product with little current consumer information about personal willingness to pay. Consumers need to be uninformed in the first period, when the toy hits the shelves in October or November, and not become informed until period two, after Christmas once lots of people have already bought the toy. Moreover, DeGraba’s model goes hand in hand with the hype theory—the more press something gets about being sold out, the more likely shoppers will believe all other shoppers are buying in period one, and thus they themselves buy in period one, continuing the cycle of sellout-hype-sellout without new customers having yet learned their actual valuation of the item.

Interestingly, in DeGraba’s model, if the monopolist were to raise the price in period one above customers’ expected valuation, the monopolist would lose the entire period one demand, as all customers would wait to buy till the second period when they learned their valuation. This implies a highly elastic demand curve when price is near period one expected valuation. However, an exogenous upward shift in the demand curve would move the expected valuation further above price, ceteris paribus, decreasing the point elasticity. Therefore, we actually have the opposite hypothesis for DeGraba’s theory—observing more elastic demand at a higher demand level supplies evidence against the theory.

Tabarrok himself offers a simple answer to the hot-toy problem which he calls the “Return-Policy Theory” (515). Retailers often offer a generous return policy, allowing customers to bring back a product they decide they do not want for a full refund. Tabarrok says that “If the hot toy increases in price whenever there is a seasonal shortage…retailers open themselves up to be gamed by consumers, consumers who purchase at the high price will be motivated to return the product only to buy it again at the lower post-shortage price” (515). Retailers could
potentially make exceptions to their policy during certain periods, but new policies can be expensive and hard to enforce. The Return-Policy Theory is yet another case that becomes more plausible if we can establish that the opportunity cost of keeping price below the market clearing level is not particularly huge.

Broadening the scope slightly, stepping away from the restriction of a shortage scenario, and aside from the elasticity theory, there are two main theories of pricing strategy during peak demand periods.

The tacit collusion theory states that we do not see price increases—and might even see price decreases—during peak demand periods because the benefits to tacit collusion break down and the collusive agreement becomes less sustainable (Chevalier 3). Chevalier, Kashyap and Rossi (2000) make the case:

[T]acit collusion is sustainable when the gains from defection in the current period are low relative to the expected future cost of being punished for the defection. The temptation to cheat from a collusive arrangement is highest during a temporary demand spike, because the gain from cheating is increasing in current demand, while the loss from future punishment increases in future demand. (4)

Regarding the hot-toy problem, this theory only applies to retailers, since the manufacturing end of a hit toy is usually monopolistic. We can consider the situation of two competing retailers selling the same item. Assume a simultaneous, repeating game where each retailer can either choose to sell the item at the collusive profit maximizing price, or cheat on the collusive agreement and charge a lower price. Also assume a grim trigger strategy is employed by both
retailers. Collusion is sustainable as long as

$$(\Pi_{\text{COLL}} - \Pi_{\text{NE}}) \frac{\delta}{1 - \delta} \geq \Pi_{\text{DEV}} - \Pi_{\text{COLL}}$$

where, $\Pi_{\text{COLL}}$ is a firm’s profit from sustaining the price collusion, $\Pi_{\text{NE}}$ is a firm’s profit at the Nash equilibrium, $\Pi_{\text{DEV}}$ is the one period profit from cheating on the collusive agreement by cutting price, and $\delta$ is the discount rate of future periods (Chevalier 11). In a relatively higher demand period, $\Pi_{\text{DEV}}$ increases by more than $\Pi_{\text{COLL}}$ or $\Pi_{\text{NE}}$, making cheating relatively more attractive. If more retailers choose to cheat in higher demand periods, then an increase in demand does not necessarily lead to higher prices in the short term. If applied to the hot-toy problem, this theory also gains validity through Tabarrok’s argument—the less profit that a higher price offers the more likely retailers will be to price low and increase market share. The problem with the tacit collusion theory is its questionable applicability to the hot-toy problem. Cheating on a tacit agreement involves under-pricing ones competitor(s) to steal customers and market share. But the hot-toy problem is a case of shortages. If a retailer is out of stock, under-pricing its competition does no good since it will not result in any additional sales, only smaller margins. Moreover, the tacit collusion theory is unable to describe manufacturer behavior since the maker of a sell-out toy is usually the only company making that toy.

In the loss-leader model, if retailers advertise their prices (or consumers are aware of the prices at various stores without having to go to the stores), then it is most efficient for the retailers to advertise and make a low price commitment on the highest demand items (Chevalier 4). Firms thereby can draw customers to their stores to buy the low priced item that is in high demand, and once there, the customers will ideally save themselves travel costs by completing the rest of their shopping needs at the same store. For the manufacturer, a loss-leader strategy only makes sense in a case by case basis. For Furby or Tickle-Me Elmo, consumers demand only
one, and once it is purchased their demand is zero. For game consoles like Xbox, or even for the recent hit Zhu Zhu Pets which have lots of potential amenities, the manufacturer may see loss-leader benefits—once the game console or hamster has been purchased, the buyer’s demand for Xbox games or the “Hamster Fun House,” etc., may go up. However, the applicability of the loss-leader model to the hot-toy problem is also debatable. No matter how low the price is, a popular item will not bring shoppers into a store if the store has no stock to sell. It may bring a crowd the day it is in stock—said one Slate article about the Xbox shortage, “Gaming enthusiasts camp[ed] outside electronic stores, desperate to buy the hot new game console…Best Buy enjoys the crowds”—but what about the following week when Best Buy is completely out of stock? That is not bringing in a crowd. Moreover, it is dubious that the manufacturer can generate additional sales of complementary products with a below equilibrium price—that would imply, for example, that those willing to buy the game console at a higher price were also those who demanded fewer games for it. Nevertheless, if it can be determined that charging the market clearing price results in only a small gain in short-term profits over current shortage prices, the loss-leader model becomes a more likely hypothesis.

3. The Elasticity Theory Explained and Applied to Online Retail and eBay

Chevalier, Kashyap, and Rossi (2000) discuss the general foundation of the elasticity theory: “With a fixed cost of searching, it is optimal to search more during high purchasing periods. This makes consumers more price-sensitive when overall demand is high” (3). During a shopping spree, or an exogenously high demand period, a shopper may be out to buy a number of goods and will see more prices and more stores, becoming better informed and thus making low price purchases easier. For example, say Elaine, George, and Jerry each just had twins, and
now Cosmo has to buy clothes as gifts for all six children. Cosmo’s demand for baby clothes is usually $x$, but now it is $6x$, so that finding the lowest price on baby clothes is worth much more to him, and therefore may be worth extra searching. Instead of just going to Babies “R” Us like usual, now he also goes to Target and K-Mart and finds that the clothes are cheapest at K-Mart, but the toy that Cosmo wanted to get for his own kid is cheapest at Target. Cosmo has a greater incentive to be more informed about prices, which leads him to be more price sensitive and his demand curve for baby products more elastic. Extrapolating this across the entire population during exogenously high demand periods such as the holiday shopping season, we can imagine a scenario where all consumers become more knowledgeable about prices, more price sensitive, the demand curve that retailers face flattens out, price dispersion decreases, and maybe prices even fall as markets become more competitive.

Warner and Barsky (1995) collected daily pricing data of eight products across 17 retail outlets in Ann Arbor, Michigan, between November 1, 1987, and February 29, 1988 (325). They found that prices tended to be lower on weekends (this result was robust but economically small), and found that sales (price cuts) were more frequent before Christmas than after, supplying evidence supporting the elasticity theory—retailers have to price more competitively in the face of more elastic demand.

To conceptualize Cosmo’s abstract game, Warner and Barsky use a “circular city” Salop model (345). I find a simple Hotelling model to be just as effective as it offers the same general analysis and result. Suppose there are two stores with $k$ people uniformly distributed between the stores. Store 1 and Store 2 sell the same product at prices $p_1$ and $p_2$ respectively. For a customer located at $t$, the travel cost to Store 1 is $t$ and to Store 2 is $k - t$, where $t$ is some integer from 1 to
Thus, a consumer is indifferent between shopping at the two stores when

\[ p_1 q + t = p_2 q + (k - t), \]

where \( q \) is the quantity of the good that each consumer exogenously purchases per period. Thus, the shopper indifferent between the stores is located at

\[ t^* = (p_2 q - p_1 q + k)/2. \]

If we assume each store’s marginal cost is zero, the profit of each store is

\[ \Pi_1 = p_1 q t \quad \text{and} \quad \Pi_2 = p_2 q (k - t), \]

and substituting,

\[ \Pi_1 = p_1 q [(p_2 q - p_1 q + k)/2] \quad \text{and} \quad \Pi_2 = p_2 q [k - (p_2 q - p_1 q + k)/2]. \]

Maximizing profit based on price, the best response functions are

\[ p_1 = p_2/2 + k/2q \quad \text{and} \quad p_2 = p_1/2 + k/2q, \]

and the Cournot equilibrium is

\[ p_1 = p_2 = k/q, \]

which shows clearly that as the quantity that each shopper is out to buy, \( q \), increases, the equilibrium price falls.

We know quantity demanded equals \( tq \), or

\[ q [(p_2 q - p_1 q + k)/2]. \]

To illustrate the rise in elasticity with a greater \( q \), assume \( k = 100, q = 10 \), and \( q_1 = q_2 = 10 \). Store 1 faces a total demand of 500. If Store 1 raised their price to 11, they would see a 10% fall in demand to 450. However, if \( q = 20 \) instead, the same one unit price increase would change total quantity demanded at Store 1 from 1000 to 800, a 20% fall in demand.

If we, however, consider the online market, the story is somewhat different. Instead of traveling to Store 1 vs. Store 2 to buy all \( q \), the consumer can simply send them an electronic
message to mail \( x \) amount of \( y \)—travel costs are zero. A consumer’s indifferent property is now simply

\[ p_1 q = p_2 q \]

and exogenous movements in \( q \) have no influence on which store a consumer would rather purchase from. Since there are many more than two stores online, finding which has the lowest price can be a time consuming process. We can therefore imagine a search cost mechanism that replaces the travel cost of the Hotelling model.

Pan, Ratchford and Shankar (2002) supply strong evidence that, despite its apparent ease, accessibility, and minimal time cost, online search mechanisms make the online marketplace no more competitive and price dispersion no narrower than we see at brick-and-mortar stores.

It has been hypothesized that the online medium and the internet lower search costs, making more price information available to buyers and electronic markets more competitive than conventional markets…Contrary to this expectation, however, Bailey (1998), Clemons et al. (2002), and Brynjolfsson and Smith (2000) have all found that price dispersion in electronic markets is substantial and no narrower than in conventional markets. (433)

Pan et al. question the results of these other studies since they did not control for potential price-influencing services or attributes of some stores, such as the shopping convenience, product information, pricing policy, and shipping and handling (436). Pan et al. used BizRate.com, which evaluates online retailers based on customer surveys, and reports daily prices and deal information for many retailers. They collected information on a number of electronic products like computer software, CDs, and DVDs. Their results show that retailer attributes have some
effect on price, especially the provision of product information and shipping and handling, but the effects are minimal, and a low adjusted $R^2$, in the range of 5 percent to 22 percent, “suggests that the price dispersion among e-tailers can be explained by their differences in service quality only to a limited extent” (439).

Evidence from Pan et al. shows that online consumers have no more product information than Cosmo the classical consumer, and we can hypothesize that the simple Hotelling model described above would apply to the online Cosmo as well the offline Cosmo, with search time cost replacing travel time. Thus, we can consider a simple model of search costs. Shopper $x$ has seen the price offered, $p$, at $r$ stores, and store $r_i$ has the best offer of $p_i$. Shopper $x$ will thus continue searching, i.e. look at the price offered at an additional store if

$$c_x < J[p_i, k_x] + J$$

where $c_x$ is the cost of an additional search to shopper $x$, $k_x$ is a measure of the shopper’s estimation of typical price of the product in question weighted by his information (more information means a more accurate estimate, less means his estimate is closer to $p_i$), and $J$ is the expected benefit of an additional search, or the likelihood and probable magnitude of finding a lower price offered than $p_i$. The expected benefit, $J$, is a positively related function of $p_i$, and an either negatively or positively related function of $k_x$ depending on whether shopper $x$ knows typical prices are relatively low or high. During an exogenously high demand period, $k_x$ increases in absolute value. If it becomes more positive, shopper $x$ knows he is unlikely to find a cheaper price, is less likely to conduct an additional search, and will most likely buy at price $p_i$ with an additional search or not. If $k_x$ becomes more negative, shopper $x$ knows he is likely to find the product cheaper elsewhere, so he will most probably search again and end up buying at a cheaper price. Thus, exogenously high demand periods, by improving consumers’ knowledge, increase
the likelihood they will purchase at a lower price, and we have a result similar to that of the
Hotelling model. One important difference to draw between the Hotelling model and the search
model is the link between the demand increase and the price fall. In the Hotelling model above, a
demand increase has a direct effect on willingness to travel for the lower price. In the search
model, an increase in demand exogenously affects a consumer’s information about the market,
which affects his willingness to continue searching given a current price option. Hence, the
shoppers affected are those with a high price option and a high original expected market price—
those shoppers learn they can find the product elsewhere for a cheaper price, thus search more,
and ultimately find and buy the product at the cheaper price. Hence, the important distinction is
that for price to fall in the Hotelling model, a demand shock to only the good in question is
needed, while a price fall in the search model requires a general demand shock. We can, of
course, complicate the Hotelling model by adding price uncertainty and the necessity to expend
search time for the lowest priced store, therefore making the two models more compatible. In
this case, intuition would tell us that online search should be less of an impediment than
searching brick-and-mortar stores, however, the results of Pan et al. say differently.

Do the search and Hotelling models apply to the case of eBay auctions? Searching
through auctions works differently than searching for regularly sold items because when one
finds an item he wants, he cannot click then-and-there and buy it. On eBay, auctions can span up
to ten days before they close, so if Cosmo is searching for an item auctioned with great
frequency, he will almost always find an auction in its early stages with a current highest bid
below his reservation price and much lower than the high bid on many auctions in their end
stages. However, low bids on young auctions may not be a winning strategy as you can easily be
outbid. Furthermore, once a bidder is outbid, he has to bid again, incurring further time costs,
still without the promise of a return. Thus, search costs may actually be higher for eBay auctioned items than for regular retailed items.

The dilemma shoppers face is also somewhat different. In this case, information about the market is based not on what typical prices are, but on what people are typically willing to pay. Therefore, the more shopping and bidding one does on eBay, the more information he will have about ending auction prices, and what is the least he will likely need to pay to successfully win an auction. As in the search model above, when shoppers do not have as much information, they will have a wider distribution of prices they are willing to bid, will be more likely to bid on an auction rather than continue searching for lower high bid ones, and the final bids will tend to be more spread out. When demand is exogenously high and shopper information rises, the dispersion should fall and final bids should concentrate closer around the mean as consumers know the market better and will more likely search for lower high bid auctions than bid up an already pricy auction. Also, unlike in the original search model, since search costs and time costs of purchasing on eBay are higher by nature than at classical online stores, we can expect a shopper looking for a specific item on eBay to have greater information regarding the typical amount he will have to pay than would a shopper looking at classical online stores. For example, if Cosmo bids on one auction, and then is outbid, he will have to search and bid again, incurring more time costs and gaining more information. The additional time costs may not be worth it if Cosmo’s demand for the item is low, but a higher demand means he will likely continue trying to win the item and thereby gain more information. Thus, the case of eBay may actually be more similar to the Hotelling model in that an exogenous increase in the demand for a single item rather than demand in general can directly affect a shopper’s information and thus willingness to search and final auction prices.
4. **The Data**

To test the elasticity theory and offer evidence for Tabarrok’s elasticity-based argument for why retailers do not raise the price on an item that is selling out, I use a hit toy from the 2009 Christmas season as a case study. In October of 2009, there were two main lines of toys that were promising to be the hot toys of the coming Christmas shopping season. The first was *BAKUGAN Battle Brawlers* by Spin Master, a line of collectable mini Pokemon-esque, action-figure monsters backed up by a trading card game and an anime TV series—a cool looking game appealing to pre-teen boys. The second hot toy was the *Zhu Zhu Pet Hamsters*, made by a small American toy company, Cepia LLC. The Zhu Zhu Pets, also called Go Go Pets, are battery operated hamsters that scoot around on wheels and make hamster-like gurgling and squeaking noises. Though they do not have any trading card game or TV series to increase their appeal, they have accessories that Zhu Zhu Pet fans can salivate over, like the “Hamster Funhouse,” the “Hamster Bed and Blanket,” the “Hamster Car and Garage,” and even the “Hamster Surfboard!”

There are five original Hamsters—Patches, Chunk, Pipsqueak, Mr. Squiggles, and Num Nums—and four less popular hamsters which were released later in the holiday season—Jilly, Nugget, Scoodles, and Winkie. The original five Hamsters were selling off the shelves as early as October, and, along with Spin Masters’ BAKUGAN Battle Brawlers, were hailed in the media as the toy of the season. Despite my admittedly greater personal interest in the BAKUGAN figures and game, the data available online was not adequate for my purposes. There are dozens of different BAKUGAN figurines, and no individual one was offered on eBay in significant enough quantities to yield sufficient data. Furthermore, using as the population all the Battle Brawlers sold on eBay would not work, as any one figure differs on a number of style and game play elements leaving two different BAKUGAN, like “Alto Brontes” and “Alpha Percival,”
statistically not comparable without controlling for a vast swath of subjective variables. The Zhu Zhu Pets, on the other hand, with only five main hamsters, offered plenty of data and were, therefore, the toy of choice for the case study. To further narrow my data, I decided to follow just Pipsqueak, the yellowish hamster with a star on its back.

The sample period runs from October 28, 2009, to January 22, 2010, and it has two main components: completed auction data from eBay, and retail prices and in-stock/out-of-stock data from 14 online retailers. Worth noting: when the data collection began, the Zhu Zhu pets were already popular, as discussed above. Therefore, the data does not cover the entire pre-Christmas period of the demand shock the toys received due to their popularity, but instead starts somewhere in the middle.

Retailer Data: The 14 online retailers were found through a site called TheFind.com. Users search for a specific product and the site returns a list of online retailers selling that product. I used the site and determined 14 online retailers, unaffiliated with Amazon or eBay. Data on the price offered by each retailer and whether the toy was in or out of stock were collected once per day from November 6 to January 21. December 5 data is missing for all stores due to a collection error. The 14 stores included 3 large and 11 small retailers. The three large retailers are Toys “R” Us, Wall-Mart, and eToys. Toys “R” Us boasts the top spot as “the world's leading dedicated toy and baby products retailer” with over 1,550 store locations and a complete online store (“About” 1). Toys “R” Us currently owns FAO Schwartz, KB Toys, and eToys.com (“About” 2). Under the ownership of Toys “R” Us since February 2009, eToys.com is the second major retailer. eToys.com claims it is “[w]ell-known for offering a differentiated assortment of toys…[and] is a highly respected brand with a rich heritage of innovation and growth. The site was founded in 1997 as the first online toy retailer, and by 1998, eToys.com became the third
largest e-commerce site in the country” (“eToys” 1). Wal-Mart is the third major retailer for which data was retrieved—specifically Walmart.com. “Founded in January 2000, Walmart.com is a subsidiary of Wal-Mart Stores, Inc.,” headquartered on the San Francisco Peninsula near Silicon Valley (“An Introduction”). The 11 smaller retailers are Kimmy Shop, Superhero Toys, Toy Wiz, Toy Store Inc, Cozcorp, Wall of Fame, Imperial Outpost Toys, Didgitech Toys, Virtual King, Discount Anime Toys, and Dragostand Bakugan. Kimmy Shop, Didgitech, and Wall of Fame claim to specialize in tough to find toys and merchandise. Superhero Toys sells mainly action figures and collectables. Discount Anime Toys and Cozcorp mostly sell collectable cards, especially Yu-Gi-Oh cards on Cozcorp, as well as other random toys and collectables. Toy Store Inc., Toy Wiz, and Imperial Outpost Toys all sell a general mix of toys and kids’ products. Virtual King has a smaller collection of toys, Zhu Zhu Pets and Pixar movie related toys being the most prevalent. Dragostand Bakugan sells nothing but Bakugan and more Bakugan and then a few Hamsters.

Collecting the data once each day left the possibility that Pipsqueak might come in stock and go back out of stock during the same day and never have been recorded as in stock. For the three major outlets, Wal-Mart, Toys R’ Us, and eToys, I was able to use a site called nowinstock.com, which sent me emails when the major stores had Pipsqueaks available online.

**The eBay Data:** The largest chunk of data was collected from the online auction site eBay where anyone can put up an item to sell, and anyone else can purchase it. There are three methods for selling items on eBay: The standard English auction where the bidder with the highest bid at the end of the scheduled auction time wins the item—sellers choose the starting price of the auction; the Buy it Now option, which offers an item at a certain price for a scheduled time period—a straight forward purchase; and the Best Offer option, where potential
buyers make offers above a minimum set by the seller until the seller accepts one of the offers or
the scheduled time runs out. Conducting a search of completed listings on eBay gives the
searcher all completed auction, Buy it Now, or Best Offer items over the past 15 days. Beginning
November 12, data from a random sample of 100 completed listings was collected each week
until January 21. The search would show up occasional results that were not just Pipsqueaks—
often Pipsqueak being sold with another item. All results that were not just Pipsqueak were
removed from the sample, leaving slightly less than 100 random observations each week. The
items were randomly selected using Microsoft Excel’s random number generator set to return
random numbers between zero and one. Every Thursday night, a completed listings search for
“Zhu Zhu Pets Hamsters Pipsqueak” was conducted. With 50 listings per page, the number of
pages the search returned would be multiplied by Excel’s random number generator, giving some
number between 0 and however many pages there were. 100 such random numbers were
generated. Rounding the numbers to the nearest integer, I would then go to the corresponding
search page and record the data from the top listing on the page. In the event Excel sent me to the
same page twice, I simply took the data from the second listing on the page. Figure 2 shows the
general layout of how completed listings appear on eBay.

The data collected includes: Date, Final bid (if any), Starting bid (if not sold), Price (if it
was a “Buy it Now” offer), starting price, number of bids, shipping price, estimated shipping
time (if a range was specified, say 4 to 7 days, I recorded the midpoint, 5.5), percent positive
feedback, and dummy variables for sold/not sold, top seller, and whether the method of sale was
an auction, Buy it Now, or Best offer. N/A was recorded when the data was missing from the
completed listing.
The seller’s percent of positive feedback is determined by the feedback received over the past 12 months on all transactions (that includes items the seller may have bought)—total positive feedback divided by total feedback. To be considered a “Top-rated seller,” the seller must have had at least 100 transactions and $3,000 in sales over the past 12 months, have a positive feedback of at least 98 percent, and go through the “PowerSeller program” which, according to eBay, requires a “proven track record of both quality and quantity” (“PowerSellers” and “Becoming”).

The collection method worked very well through the weeks in November and December. Many Pipsqueaks were being offered on eBay, so the population I was drawing from was significantly large. However, in January, the number of Pipsqueaks offered dropped off precipitously, and the population became small enough for me to collect it in its entirety. Therefore, the random sample is truncated at approximately the New Year. I recorded weekly total completed listings from Saturday to the following Friday during the time period, and recorded any completed listings that popped up from the search that were not just Pipsqueaks. That gave me a gauge of how many Pipsqueaks were being offered on eBay per week. See Figure 3 for an approximate measure of supply.

5. **Descriptive Statistics**

**Retailer Data**

Daily pricing data and in stock/out of stock data was collected from 14 online retailers over the time period of November 6, 2009, to January 21, 2010—giving 76 observations for each retailer. Table 1 displays the mean and standard deviation of the prices offered by the 14 retailers before Christmas, after Christmas, and over the entire period. Imperial Outpost Toys’ post-
Christmas data is not available as the store never had Pipsqueaks in stock nor a price quote during the period.

Only Kimmy Shop and Toy Store Inc. have a higher average price after Christmas (see Table 1). It is worth noting that Kimmy Shop maintained a price quote for the Pipsqueaks at $24.99 during the entire pre-Christmas period, but they did not get any in stock until after Christmas (See Figures 4 through 17 for comparative pricing, date, and in/out of stock data). This result of lower prices after Christmas is similar (though slightly more dramatic) to the results Warner and Barsky found as an average across their goods observed (Warner 329). Post-Christmas data make for just 35.67% of the sample. Considering Figures 4 through 17, price changes were mostly non-existent among the three major retailers, with eToys making the only pricing change, while smaller retailers had a wider range of prices.

Figures 4 through 17 show price changes over time for each store, as well as time series data for when the store had pipsqueaks in stock. Some stores maintained a quoted price even while they were out of stock, others had no price quote when they had no stock, which shows up as just empty space on the charts. The blue bars represent price charged that day, while red marks at the bottom show periods when Pipsqueaks were in stock. As mentioned in the previous section, data for all stores is missing on December 5 due to a collection error. The number and frequency of price changes varies dramatically depending on the store. Prices also do not seem to change during periods where a store is out of stock, which makes sense as a quoted price is not greatly meaningful when there is no stock to sell, and the retailer has no reason to be changing price. Since the three large outlets rarely had Pipsqueaks in stock, (Walmart was never recorded as having Pipsqueaks in stock), it could be argued that it is unsurprising that we see stagnant prices, since they have no stock to change their prices on. However, from the data taken from
nowinstock.com, we do know that over the course of the season, Toys “R” Us, Walmart.com, and eToys all had the toy in stock on an irregular basis, but, unlike the smaller stores, the stocks of the three large retailers would run out quickly—within one day—such that the in/out of stock data would be collected during times the Pipsqueaks were not in stock, and recorded as such, even though they may have been in stock earlier or later the same day. Thus, in Figures 4, 5, and 6, for Toys “R” Us, Walmart, and eToys, respectively, dark blue marks at the bottom of each chart mark the days for which nowinstock.com alerted me that Pipsqueaks were in stock at that online retailer. This largely refutes the claim that we do not observe any price changes from Toys “R” Us or Walmart simply because they never had anything in stock in the first place. Also, as seen in Figures 7 through 17, price changes were much more frequent before Christmas and for the most part prices were higher. There are 111 total price changes across all stores, but only 13 post-Christmas, so that while post-Christmas observations make up 35.5% of the data, only 11.7% of the price changes happen during this period, and only one of those 13 price changes (Kimmy Shop) is a price increase.

**eBay Data**

As mentioned, eBay completed listings data were collected from October 28, 2009, till January 20, 2010. Table 2 displays descriptive statistics of the eBay completed listings information on final price and full price (final price + shipping cost) over the course of the time series data for auctions and Buy it Now completed listings. Only 10 data points for Best Offer completed listings were collected using the random data collection method described earlier over the entire collection period. Therefore, the Best Offer option will be dropped from the sample. Moreover, there were only six completed listings of sold items of Buy it Now offers after Christmas, so Buy it Now data is excluded from Table 2. Figure 18 is a chart of the average price
of Pipsqueaks from the beginning of the collection period until Christmas, and displays a clear price trend—final auction prices rising through much of November, and flattening off towards the end of November and very beginning of December, then declining rapidly until Christmas. This trend line is reflected in a good portion of the retailer charts of price over time.

The average price of all completed auctions is $25.28, and the average full price is $30.35. These are each $1 lower than the same statistics for just the pre-Christmas sample because of the way the data is heavily weighted on the pre-Christmas side. As mentioned earlier, after Christmas, and especially moving into January, the number of Pipsqueaks offered for sale on eBay dropped off precipitously, and very few of those offered were purchased. Thus, the useful data falls off after Christmas, and, as Table 2 shows, there are only 39 observations of sold auctions in the post-Christmas data. Nevertheless, the post-Christmas prices are clearly and dramatically lower than pre-Christmas prices—average final price is $12.67 less after Christmas, a 48.5% price drop, and average full price is $12.99 less after Christmas, a 41.6% price drop. So we find here evidence that the pre-Christmas period may be a peak demand period compared to the post-Christmas period, both in more purchases and in higher final auction prices—people are clearly willing to pay more for a Pipsqueak before Christmas than after.

Pre- and post-Christmas average Buy it Now Price and Full Price are comparable to the average auction prices, showing up only slightly greater.

6. **Determining the Peak Demand Period**

To test the elasticity theory, we want to see if price dispersion is less in peak periods than in non- or lesser peak demand periods. However, the first step in making any comparisons
between peak periods and non-peak or lesser peak periods is to establish just what those periods are.

**Weekends**

One preliminary step would be to copy Warner and Barsky, and consider weekends as mini-peaks, however, their data was collected from brick and mortar stores, while mine was from online retailers and eBay, which calls for perhaps a slight erratum to the assumption that weekends represent small demand peaks. Warner and Barsky assume that the theory holds, then look at retailers’ weekday vs. weekend price changes to determine if the theoretically higher demand on weekends results in an increase in price cuts. They find a significant negative weekend effect on price level, if small in absolute magnitude, displaying some evidence that retailers face a more elastic demand curve on weekends. If we accept the assumption that weekends represent mini-peak demand periods, Warner and Barsky’s results support the elasticity theory that argues consumers will be more price sensitive during high demand periods. I question, however, the applicability of treating weekends as higher demand periods when in the context of *online* retail. Online retailers are accessible at all hours of the day and night, meaning shoppers can return home from work and leisurely buy products online from the comfort of their living room couch. Shopping at brick and mortar outlets requires a greater investment of time, which consumers may not be willing to suffer after returning home from work on a weekday. Furthermore, not all brick and mortar stores are open at night and shopping at them may not be an option for some people during the week. Finally, online shopping can be accomplished at work for many people, further breaking down the weekday shopping barrier. Therefore, online retailers may not see a small spike in demand during weekends.
Consider eBay first. Weekday data includes all data taken on Mondays, Tuesdays, Wednesdays and Thursdays. Weekend data includes Fridays, Saturdays, and Sundays. Buy it Now items have slightly higher prices on weekends; average full price is $4.09 (12.4 percent) higher, and the coefficient of variation (standard deviation divided by mean) is 3 percent lower—weakly supportive of the elasticity theory that price dispersion will fall during peak demand periods as consumers are more price sensitive (see Table 3). The auction data is somewhat different since buyers bid up the price rather than accept or reject a price offered by the seller. Nevertheless, if weekends represent mini-peak demand periods, the analysis should be the same—bidders should bid up the prices more on weekends, ceteris paribus, (since the end of the auction is when the greatest percent of the bidding happens), and the elasticity theory implies lower price dispersion (Ockenfels 3). The data however show the opposite; average full price falls by 2.35045 (7.5%) on weekends, and the coefficient of variation falls 16.06%. Again, these weekend results are not entirely shocking for the same reasons discussed above—we are looking at online sales, meaning consumers do not face the same time and convenience constraints faced when shopping at brick and mortar stores. The case could be made, however, that average final prices could fall on weekends despite a higher demand because the supply of Pipsqueaks offered increases. Steiner (2004), surveying almost 1000 eBay sellers, found evidence that weekends, specifically Sundays, are the most popular time to end an auction—57.5 percent of respondents said Sunday was the optimal ending time. Unfortunately, total daily number of completed listings for Pipsqueaks was not collected, so I am unable to do a quantitative analysis of weekend Pipsqueak supply.

We can also use regression analysis as an additional test of the importance of weekends on final auction prices on eBay. I regressed full price of all completed auction listings on dummy
variables for each day of the week—the EViews results are presented in Figure 19, and Figure 20 shows the difference between the estimated coefficient for each day of the week and the average full price of the sample. To avoid perfect multicollinearity the constant term was dropped from the equation. All coefficients are significant at the 1% level. Again for Friday, Saturday, and Sunday we observe lower final full prices for completed auctions than we do for weekday completed auctions.

My data on the 14 online retailers is relatively similar to Warner and Barsky’s, and I am able to make similar tests as they of the price-effect of weekends. Table 4 displays weekend vs. weekday data over the entire sample period for each online retailer and the combined total. The total shows that weekend prices are slightly lower than weekday prices. Weekday average price across all 14 retailers is $29.41, while weekend average price is $28.81. This is consistent with Warner and Barsky’s results (pages 335, 341, and 342), and though the difference in my aggregate results is slightly smaller, Warner and Barsky also found the magnitude of weekend markdowns to be economically small.

If the major retailers (Toys “R” Us and Walmart, who rarely had Pipsqueaks in stock and showed no price changes, and eToys, who had only one price change) are removed, as well as Kimmy Shop and Imperial Outpost Toys, who both had less than three price changes and had the toy in stock for less than a third of the data collection period, the weekend average price becomes $34.40, and weekday average price is $34.92—the difference in not statistically significant at the 10 percent level of significance. In this case, the margin shrinks to being economically insignificant, and it is difficult, based on these results to claim that online retailers see a different demand curve on weekends. This ultimately disagrees with Warner and Barsky’s conclusion that
weekend demand is more elastic and retailers offer more competitive prices as a consequence. However, for all the reasons above described, this result I do not find surprising.

We can also look at the retailers’ price changes by day of the week. Figure 21 displays the cumulative price change occurring each day of the week over the entire period. Interestingly, this data displays much more evidence for the theory that sellers face a different demand curve on weekends and drop price accordingly on the weekend. Mondays, Tuesdays, and Wednesdays display a general increase in prices, while Thursdays, the day before the weekend, show a significant decrease in prices. Fridays and Sundays also display a decrease in price, though price changes on Saturdays generally seem to be price increases. This is more supportive of Warner and Barsky’s results, though certainly not robust evidence. We can also conduct a similar analysis by considering price regressed on dummies for each day of the week—a nearly identical procedure to that done by Warner and Barsky (Figure 22 shows the EViews regression results). Again the constant term was dropped to avoid perfect multicollinearity. Figure 23 shows the difference between the coefficient for each day of the week and the average price across the entire season. Toys “R” Us, eToys, Walmart.com, Kimmy Shop, and Imperial Outpost Toys were eliminated from the sample for reasons discussed above. The result is very similar to that of Warner and Barsky—a higher price on weekdays, with price dropping on Thursday through Saturday, and beginning to rise again Sunday. If we accept the mini-peak weekend demand theory, we could infer that retailers are reacting to a higher elasticity by cutting prices on weekends.

Unfortunately, after siphoning through several theories and contradictory and/or inconclusive evidence in the eBay data, it cannot be said with any level of confidence that the mini-peak demand on weekends theory holds for eBay auctions, and therefore, any weekend vs.
weekday price dispersion tests of the eBay data are of little use in analyzing the hot-toy problem. This leaves a potentially interesting result found in the retailer data somewhat useless.

**Pre-Christmas vs. Post-Christmas**

An easy step would be to just look at pre- vs. post-Christmas data. However, only 39 observations were collected after Christmas, and for all data points collected after January 7, there were fewer than 100 hits based on my completed listing search and I was able to collect the entire population. Nearly all items that showed up in this period were not just Pipsqueak listings—instead usually a Pipsqueak and another hamster or two, like a Chunk and a Mr. Squiggles being sold together as one—and had to be eliminated from the sample. After January 7, my search found only six singular Pipsqueaks offered, and only two were sold, at prices of $7.99 and $10.55. Hence, we cannot learn much about post-Christmas demand movements other than that demand falls off precipitously. Therefore, simple pre- vs. post-Christmas analysis will not be useful, so high pre-Christmas vs. low pre-Christmas estimated demand will need to be the contrasted time periods.

**Higher Peak Demand vs. Lower Peak Demand**

Warner and Barsky used the days between Thanksgiving and Christmas as their comparative high demand period. Chevalier et al. studied supermarket purchases, and arbitrarily chose the three week period from the week before Christmas to the week after to include for pre-New Years shopping demand. For my data however, we could expect the highest part of the peak demand period to drop off a bit over a week before Christmas because of necessary shipping time. Perhaps the most compelling argument for Pipsqueak eBay demand movements would contend that equilibrium demand over time should be a concave polynomial maximizing a week or two before Christmas. This would make sense as a Pipsqueak is worth more if bought before
Christmas and can be given as a gift on Christmas day. We can also imagine a possible bump along the trend line for Hanukkah. If we use eBay final auction prices as an estimator for movements in willingness to pay, and use that to infer general movements in the demand curve over the season, Figure 18 offers some interesting insights. It displays, as expected, a concave pre-Christmas full price trend. However, the peak appears to be sometime in late November—much earlier than expected given shipping speeds average 5.5 days over all observations and only 18 of the 609 observations have estimated shipping time of over 10 days. Thus, shipping speed alone offers little reasoning for why the estimated demand appears to drop off so early. Even Hanukkah is too distant (begun on December 11) for shipping time to play a major role in the early drop off in willingness to pay, though one could argue it plays a part in the continued fall in price.

Possibly the most convincing argument for the early drop off in price is a supply based argument—that an increase in the number of Pipsqueaks being offered for auction drove prices down. As mentioned earlier, the total number of completed listings results found by my weekly search was recorded. From each weekly random sample, the percent of observations that were usable (i.e. just a Pipsqueak, not a Pipsqueak and a Chunk for example) can be multiplied by the total number of results found for that week to give an estimate of the total number of Pipsqueak auctions completed each week on eBay, in other words, the supply. So for example, if an eBay completed auction search for Pipsqueaks were to return 5,000 hits completed in the past week, and of a random sample of 100 items from that week, 90 were usable observations (just Pipsqueak), then the projected supply of just Pipsqueak items that week would be 4,500. Figure 2 compares the week by week average full price over the season with week by week supply. Indeed, we find strong negative supply/price movement during the late November period—
supply shoots up 359 percent to over 6000, while average full price begins to fall after five
weeks of rising. Price continues to fall until finally flattening out around the same time that
supply crashes back down. However, other than the two large supply movements separated by
three weeks, price seems to move entirely unrelated to supply. In fact, the estimated weekly
supply appears to mimic the weekly average price, but about two weeks behind, and since less
than 20 percent of eBay auctions last longer than seven days, this suggests that price is
influencing supply more than vice versa (Chou 4). Moreover, if we look at the prices of the nine
retailers who had more than one price change over the sample period (Figures 9 through 17), we
find a similar trend as the eBay data, with prices rising and falling around similar dates. These
retailers are unaffiliated with eBay, and a change in the number of Pipsqueaks offered on eBay
should not have a strong influence on their pricing decisions. Therefore, seeing a similar pattern
in both the retailers and on eBay implies that there is an exogenous increase in demand during
mid to late November. While there appears to be some supply influence on final auction prices, it
certainly is not telling the whole story. Nevertheless, it could be part of the reason why final
auction prices appear to fall before expected. There are several other possible explanations for
the early drop in willingness to pay: (1) shoppers spent more time at brick and mortar stores
thanks to post Thanksgiving sales, and thus eBay auctions got less attention; (2) the toy simply
became less desired; (3) the false rumor that the Zhu Zhu Pets contained unsafe levels of
antimony, which hit CBS news first on December 5, may have given a second wind to an
otherwise slight price drop (“Zhu Zhu Hamsters May Pose”).

We can also consider the week by week percent of auctions sold, or equivalently the
percent of auction items that received at least one bid, to determine the period in which shoppers
are the most vigorous searchers. Figure 24 displays the weekly percent of sold auctions over the period. We find again a similar peak period, though somewhat wider in both directions.

One final measurement we can use to identify the highest demand period is the number of bids per auction. Figure 25 shows the trend in number of bids per auction over the season. Once more we see the usual shape, though less pronounced, and it is not very clear where exactly the high period begins to tail off.

Also, to help determine specific starting and ending days of the peak demand period, I determined day by day average full price (Figure 26). From this graph we can see that on November 12, average full price jumps above $35, where it remains without any significant up or down trend until December 2 when if falls back down below $35. On either end of this section there is a clear up/down trend. Moreover, from the previous evidence, the supply argument is the only one that does in fact dispute this period as the highest period of the pre-Christmas peak demand period. Furthermore, while an increase in supply during the seven day period of November 28 to December 4 may have some causal relationship with the subsequent drop in final auction price, it is unclear its extent and where exactly that effect begins, and we cannot, therefore, say a fall in willingness to pay is not in fact the reason for the drop in price. It is, thus, not unreasonable to say that the population of bidders during this period, November 12 to December 2, is that which appears to have the highest demand for Pipsqueaks. Perhaps during this period consumer information has reached its apex—enough children have seen and know about the toy that they are begging their parents for one—or perhaps parents are willing to pay a premium during this period because they are worried they will not be able to get a hamster later, or that prices will keep rising even higher. Hence, I propose the period of November 12 to December 2 as the highest peak demand period, which can then be compared to all other periods.
To test if the average full price during the chosen period is significantly greater than the average of all other times, a simple t-test can be used. The null and alternative hypothesis are

\[ H_0 : m_1 = m_2 \]
\[ H_A : m_1 > m_2 \]

Where \( m_1 \) is the mean of the full price of all observations sampled between November 12 and December 2, and \( m_2 \) is the mean of all other observations. We find, \( m_1 = \$38.8 \) and there are 231 observations in the sample, and \( m_2 = \$25.79 \) with 363 observations. The difference in means is 13.01 and the estimate of the standard error is approximately 0.5, thus giving a t-score of 26.02, which, with 592 degrees of freedom, shows that \( m_1 \) is greater than \( m_2 \) at the at the 1% level of significance. This supports the use of November 12 to December 2 as the period of highest demand.

We can use the number of bids per auction as an additional test of consumer activity during my proposed peak demand period. The search model predicts that price dispersion will decrease during peak demand periods because that is when consumer knowledge is greatest due to increased searching and bidding. Consider the following OLS estimation,

\[ \text{NB}_i = \beta_0 + \beta_1D_i + \beta_2FSP_i + \epsilon_i \]

where \( \text{NB}_i \) is the number of bids on auction \( i \), \( \beta_0 \) is a constant, \( D_i \) is a dummy variable equal to one if the auction was completed between November 12 and December 2 inclusive, and zero otherwise, \( FSP_i \) is the full starting price (starting price plus shipping cost), and \( \epsilon_i \) is a standard stochastic error term. The null and alternative hypotheses are

\[ H_0 : \beta_1 = 0 \]
\[ H_0 : \beta_2 = 0 \]
\[ H_A : \beta_1 > 0 \]
\[ H_0 : \beta_2 < 0. \]
We expect $\beta_1$ to be positive because higher demand should result in increased bidding, and $\beta_2$ to be negative because the higher the beginning bid, fewer additional bids should be placed before the high bid reaches consumers’ willingness to pay. The EViews output is reported in Figure 27.

The results are

\[
\text{NB}_i = 14.44241 + 4.31007\text{D}_i - 0.39689\text{FSP}_i \\
(0.38355) \quad (0.42598) \quad (0.02512) \\
t = 37.65703 \quad 10.12718 \quad -15.79763 \\
\text{Adjusted } R^2 = 0.347209 \quad n = 576.
\]

The coefficients are statistically significant at the 1 percent level in the predicted direction, so we can reject the null hypothesis in both cases, and find evidence that holding staring cost constant, the number of bids per auction increase during the projected peak demand period, implying bidders are in fact more active and therefore more informed. (An additional regression was run including an interaction term of $\text{D}_i*\text{FSP}_i$. The term was insignificant and the coefficients and Adjusted $R^2$ changed minimally). This further supports the use of November 12 to December 2 as the highest demand period. However, this result should be not be given too much weight. The number of bids is a somewhat flawed tool of measurement since, even holding starting price constant, it is largely based on how high bidders bid above the previous bid. Also it is likely influenced by eBay’s bidder reserve mechanism, where a bidder can specify the maximum they are willing to bid, and if his or her current bid is out-bid, eBay will bid automatically place a new bid at one dollar higher, continuing this up until the specified reserve. Therefore, much of the observed increase in bidding activity may actually not be related to additional bidder activity and subsequent gains in bidder information.
7. **Coefficient of Variation as a Test of the Elasticity Theory**

As discussed earlier, the main method we are able to use to estimate changes in elasticity is through changes in the dispersion or variance of final auction prices. A flatter demand curve means consumers are more sensitive to price, and will search more for the lowest priced item. With increased searching, we would expect fewer auctions with a small high bid to go unnoticed, and thus they are bid up closer to the average. We would also expect to see fewer expensive high bid Pipsqueaks to receive additional bids, as more consumers instead search for and bid on lower high bid auctions. Therefore, we would expect the dispersion of final auction prices to decline, and the standard deviation to shrink during the period of November 12 to December 2. On the other hand, if the elasticity theory is untrue or does not apply in the case of online purchases, we would expect no change to the price dispersion over the entire sample period. As a preliminary step, a simple F-test can be used on the standard deviation of the two different data periods. The hypothesis are

\[
H_0 : S_1 = S_2 \\
H_A : S_1 < S_2,
\]

where \( S_1 \) is the standard deviation of full price for all completed auctions in the estimated highest demand period, and \( S_2 \) is the standard deviation for all other completed auctions. The test statistic in this case is just \( S_2^2 / S_1^2 \). From the data we find \( S_2^2 = 50.84 \) and \( S_1^2 = 25.57 \), so \( F = 1.99 \). This is greater than the critical value for the 1 percent level of significance, so we can reject the null hypothesis that the standard deviation is not less during the estimated peak demand period.

However, there is good reason for this result to be questioned. First, the estimated peak demand period was chosen because it is where full price appears to reach it apex, while the before November 12 and after December 2 full price follows a clear up and down trend, demand
appearing to increase or decrease over time (consider figure 26). If the true mean of the full price is in fact inconstant over time, then variation around the mean of the entire sample is not entirely random. Thus, holding random variance around the true mean constant, we would expect a larger variance around the sample mean than we would if the true mean was constant. Second, if the sample mean is unreflective of the true mean, then the overall sample standard deviation tells us nothing in-and-of-itself about the price dispersion or consumer price sensitivity.

To fix this problem, we can break the sample down into day-by-day means and standard deviations to account for fluctuations in the true mean, and then run a simple regression using the per day coefficient of variation (standard deviation of day $i$ divided by mean of day $i$) as the dependant variable. The estimated OLS regression is

$$SD_t/Avg_t = a_0 + a_1 D_t + \epsilon_t,$$

where $SD_t/Avg_t$ is the day-by-day coefficient of variation, $a_0$ is a constant, $D_t$ is a dummy variable equal to one if the date was between November 12 and December 2 inclusive, and zero otherwise, and $\epsilon_t$ is a standard stochastic error term. The null and alternative hypotheses are

$$H_0: a_1 = 0$$

$$H_A: a_1 < 0.$$  

I chose to use the coefficient of variation, a customary measure of price dispersion (Sorensen [2000], Carlson and Pescatrice [1980]), instead of standard deviation because we are interested in the degree of price variance in each period regardless of differences in the mean—we want to know the relative difference in price dispersion between the higher and lower demand periods rather than the absolute difference (Baye 467). For example, a standard deviation of 5 around a mean of 40 implies much more relative price sensitivity than a standard deviation of 5 around a
mean of 10. All days with fewer than four observations were removed from the sample. I used EViews to estimate the equation. The EViews results are reported in Figure 28. The results are

\[
\frac{SD_t}{Avg_t} = 0.147647 - 0.035742D_t \\
(0.012522) \quad (0.020264)
\]

\[t = 11.79141 \quad -1.763809\]

\[Adjusted \ R^2 = 0.037622 \quad n = 55.\]

The coefficient \(a_1\) has the expected negative sign, and with 54 degrees of freedom, the critical value for a one sided t-test at the 5 percent level of significance is 1.673565. Since the absolute value of the t-statistic for \(D_t\) is 1.763809, which is greater than 1.674689, we can reject the null hypothesis at the 5 percent level of significance. Moreover, the magnitude of the estimated coefficient of \(D_t\) is quite substantial. The mean of all of the observations of \(SD_t/Avg_t\) is 0.136226, and the estimated \(a_1\) is 0.035742. Thus, we find that the estimated coefficient of \(D_t\) is 26.24 percent of the mean of \(SD_t/Avg_t\) —implying that there is a 26.24 percent decrease in the price dispersion when in the highest region of the peak demand period compared to the sample as a whole. The fit of the equation is quite small, but that is not particularly surprising given the imprecise nature of how the most-peak demand period was determined. Nevertheless, if the estimated highest peak demand period is reasonably correct, we find fairly sound evidence that price dispersion does in fact decrease during this highest demand period relative to the other periods, implying that when consumers’ demand for Pipsqueaks increases, their price sensitivity and willingness to search increases as well. Thus, we find support for the elasticity theory as well as Tabarrok’s elasticity argument for why retailers and manufacturers may have less of a profit incentive for raising price than a first glance observation may lead one to believe.

One potential problem with the regression results is the presence of serial correlation. The Durbin-Watson d-statistic for the estimated regression is 1.42 and the lower critical d-value at 50 degrees of freedom is 1.5 (Studenmond 617). Thus, there may be moderate serial correlation in
the residuals, which could mean the estimates of the standard errors are negatively biased, increasing the likelihood of a type-1 error. To correct for the potential bias, the equation can be re-estimated using the AR(1) Generalized Least Squares method. The results of the GLS estimate are

\[
\frac{SD_t}{Avg_t} = 0.154422 - 0.042175D_t \\
(0.014376) \quad (0.022081) \\
t = 10.74150 \quad -1.910011 \\
\text{Adjusted } R^2 = 0.039632 \quad n = 51.
\]

(EViews results are listed in Figure 29). The results of the original estimated equation appear to be robust in the face of potential serial correlation. The coefficients and the standard errors of the GLS estimate increase slightly over those of the original estimate, and the t-statistic for \( a_1 \) increases, so the null hypothesis can still be rejected at the 5 percent level of significance.

Though day-by-day pre- and post-Christmas standard deviations in the full price cannot be measured due to a lack of data in the post-Christmas period, we can compare the periods as whole blocks, or do a week by week analysis. Table 2 shows that there is actually a decrease in the standard deviation in the post-Christmas data, dropping from 8.89 to 7.04, which is the opposite of what we would expect. However, if the coefficient of variation is considered instead, we find the post-Christmas price dispersion to be much higher than that of pre-Christmas, increasing from 0.2847 to 0.3829—what we would expect under the elasticity theory. Moreover, if we consider week by week averages of the full price we find an even more visually striking result. Consider Figure 30, and Table 5 (weeks are considered Monday-Sunday). In all weeks, except October 28 to November 1 (a partial week because data was not collected before October 28), and the week of December 21 to December 27, the two weeks with the fewest observations, we see that the coefficient of variation moves noticeably opposite to the average full price. Moreover, in the week after Christmas, when not only our estimated highest peak period is over,
but the entire peak demand Christmas shopping season has ended, there is a dramatic jump in price dispersion. It would be helpful to see if this higher dispersion remains the trend in subsequent weeks after Christmas, but unfortunately the available data disappears. Nevertheless, this offers additional evidence supporting the elasticity theory.

If we disregard the evidence against the mini-peak weekend demand hypothesis, and assume it is true, we can use the same regression method to test changes in relative standard deviation on weekends vs. weekdays. The estimated OLS regression is

$$\frac{SD_t}{Avg_t} = a_0 - a_1DW_t + \epsilon_t,$$

where $SD_t/Avg_t$, $a_0$, and $\epsilon_t$ are the same as before, and $DW_t$ is a dummy variable equal to one if the observation is from a Friday, Saturday or Sunday, and zero otherwise. The null and alternative hypothesis are the same as before, as are the sample restrictions. The OLS regression estimate is

$$\frac{SD_t}{Avg_t} = 0.130000 - 0.008800DW_t \quad (0.013692) \quad (0.020308)$$

$$t = 9.494829 \quad 0.433326$$

$$\text{Adjusted } R^2 = -0.015271 \quad n = 55.$$ (EViews results presented in Figure 31). Unsurprisingly, since the theory was weak, the results are poor with $a_1$ having the wrong sign and a statistically insignificant t-score. The null hypothesis can, therefore, not be rejected and the previous conclusion that the weekends do not represent mini-demand peaks in the eBay market for Pipsqueaks is further supported. This is unfortunate because we found some evidence, though admittedly not strong evidence, that the 14 retailers cut price more often and in greater magnitude on weekends, (consider Figures 21 and 23). If eBay supplied evidence that demand rose on weekends, we could interpret the retailers price movements as evidence that they were responding to greater elasticity of demand on weekends potentially due to the higher demand. However, the eBay data gives no reason to
believe that weekends actually act as small-peak demand periods nor that shoppers are more price sensitive on weekends. Hence, we can learn little of use from the retailers’ day-by-day price changes.

**Supply as a Potential Counterpoint**

The issue of supply is a potential counterpoint to the significance of my results. Baye, Morgan, and Scholten (2004) tested to see if the number of sellers offering a particular item influences the price dispersion of that item. They used a popular price comparison site called Shopper.com and looked at the prices of the top 1,000 products over an eight month span. They found that “the number of firms listing prices for these products varies a great deal—both cross sectionally and over time” (Baye 464). Moreover, “the level of price dispersion is greater when small numbers of firms list prices than when large numbers do” (465). Therefore, if we were to see a greater number of Pipsqueak auctions being completed during the estimated peak demand period, then, given evidence from Baye et al., one could make the case that the negative coefficient of $D_t$ is due to greater supply rather than higher demand. However, consider once more Figure 3; there are three distinct weeks, from November 28 to December 18, where the number of completed Pipsqueak auctions is greater than 6,400, while all other weeks the same statistic is less than 2,700—a clear break. Moreover, while this 21 day high supply period overlaps the highest and less-high demand periods, 16 of the 21 days fall in the less-high demand period. Hence, if supply is playing a role in price dispersion, then it should actually work to decrease price dispersion more in the less-high demand periods than in the high demand period! Evidence from Baye et al., therefore, increases the significance of my results; even with supply-induced downward pressure on price dispersion during the less-high demand period, price dispersion is still statistically significantly less during the highest demand period! Additionally,
since the conventional definition of price dispersion that Baye et al. use is not the same as mine, it is not necessarily clear that their results should cross over to my data or vice versa. They consider the dispersion of prices offered by firms irrespective of what consumers buy, and their “supply” is the number of firms listing prices. I consider the dispersion of prices at which individual items are bought, and my “supply” is the number of completed auctions. Therefore, price dispersion in my data is primarily a product of consumer behavior, while price dispersion in their data is determined more so by suppliers, and comparing results across the two data sets may be erroneous.

8. Conclusion

Theories have been suggested for why retailers and/or manufacturers do not raise the price of a sellout hot-toy to the market clearing level. Other than DeGraba’s theory of contrived shortages, the plausibility of all these theories rests heavily on the opportunity cost of not raising price—how much profit are manufacturers and retailers forgoing by maintaining a shortage? The greater the benefit of raising price and capturing a larger margin, the more likely that benefit outweighs the theorized costs or benefits of doing or not doing so. Tabarrok argues that the larger the shortage, the more elastic the demand curve and the less additional profit a price increase would create. Similarly, the elasticity theory vies that as demand rises for a specific good or in general, consumers become more elastic and therefore sellers tend to offer sales more often—or in the hot-toy case, not increase price. My analysis supports Tabarrok’s argument and the elasticity theory. Using the eBay data, I was able to determine an estimated highest demand period within the pre-Christmas data. A variance test showed a statistically significant decrease in the coefficient of variation of full price when in the highest demand period, and a simple OLS
regression of the day-by-day coefficient of variation on a dummy variable for days within the
highest demand period gave a negative coefficient of 0.035742, significant at the 5 percent level.
The magnitude of the decrease in the coefficient of variation during the highest peak demand
period was equivalent to 26.24 percent of the mean of the dependant variable. Moreover, despite
limited post-Christmas data, what is usable shows a clear increase in the coefficient of variation
after Christmas. Using movements in the price dispersion as an estimator for directional
movements in the price elasticity, my results supply evidence that the highest demand period is
coupled with greater elasticity. Ultimately, I find support for Tabarrok’s argument that increasing
the price of a sell-out toy may result in only small short-term profit gains.

Several worthy objections can be made against my somewhat irregular method of testing
the elasticity theory as evidence for or against Tabarrok’s theory. First, one can argue that the
elasticity theory, like the tacit collusion and loss-leader theories, is not applicable in peak
demand cases involving shortages. One line of the elasticity theory reasoning says that
consumers are more elastic during peak periods because if one store raises price they can go to
another store and buy it for a cheaper price, but this does not work if there are shortages. Price
differences at stores are irrelevant if both are out of stock. The advantage of my method is that I
use the secondary market, eBay, to be able to estimate the direction of movements in demand
and elasticity beyond the point of the shortage. I cannot measure elasticity at the current
shortage-inducing price, but that was not my goal. Instead I seek to identify the direction of
movements in elasticity given the direction of movements in demand. Likewise, objections can
be raised about using eBay completed auction prices as an estimator of demand, and the standard
deviation and coefficient of variation as estimators of elasticity. However, again, my objective is
not to measure the magnitude of the demand or elasticity, but merely their co-movement and
whether or not there appears to be a negative relationship. While an increase in the average final auction price of the Pipsqueaks does not inform us of the extent to which demand changed, it does imply that more people are bidding and higher bids are being placed on the same items—suggesting demand has increased.

A useful extension of this work would be to consider prices offered on other secondary market sites like Amazon and Craigslist, or to look at co-movements of a hot item and its complements, such as a game console and the games that go with it, or Pipsqueak and the Hamster Fun House. Also, it may be interesting to compare holiday season demand and price dispersion movements of a hot toy with those of a non-hot toy, but finding a non-hot toy with enough auction offers on eBay may be difficult.
Appendix

Figure 1
Taken from Tabarrok’s “Hot-Toy Problem, page 514.
Figure 2
Format of Competed Listings as Displayed on the eBay Website

Figure 3
Weekly Average Full Price and Number of Completed Listings
<table>
<thead>
<tr>
<th>Retailer</th>
<th>Total</th>
<th>Pre-Christmas</th>
<th>Post-Christmas</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Toys “R” Us</strong></td>
<td>Mean</td>
<td>9.990000</td>
<td>9.990000</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td><strong>Walmart</strong></td>
<td>Mean</td>
<td>8.000000</td>
<td>8.000000</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td><strong>eToys</strong></td>
<td>Mean</td>
<td>11.69732</td>
<td>15.37462</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>3.809488</td>
<td>5.188745</td>
</tr>
<tr>
<td><strong>Kimmy Shop</strong></td>
<td>Mean</td>
<td>26.15883</td>
<td>24.99000</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>4.464487</td>
<td>0.000000</td>
</tr>
<tr>
<td><strong>Digitech</strong></td>
<td>Mean</td>
<td>43.62461</td>
<td>52.15563</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>16.64433</td>
<td>15.50261</td>
</tr>
<tr>
<td><strong>Dragostand-Bakugan</strong></td>
<td>Mean</td>
<td>29.12526</td>
<td>33.49917</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>8.868978</td>
<td>7.911047</td>
</tr>
<tr>
<td><strong>Superhero Toys</strong></td>
<td>Mean</td>
<td>31.13474</td>
<td>36.65667</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>10.55740</td>
<td>9.135699</td>
</tr>
<tr>
<td><strong>Wall of Fame</strong></td>
<td>Mean</td>
<td>39.96183</td>
<td>44.71093</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>14.27583</td>
<td>13.82945</td>
</tr>
<tr>
<td><strong>Virtual King</strong></td>
<td>Mean</td>
<td>37.62158</td>
<td>42.69833</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>13.20287</td>
<td>14.29024</td>
</tr>
<tr>
<td><strong>Cozcorp</strong></td>
<td>Mean</td>
<td>23.77961</td>
<td>29.51354</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>10.11902</td>
<td>8.500386</td>
</tr>
<tr>
<td><strong>Toy Store Inc.</strong></td>
<td>Mean</td>
<td>29.34474</td>
<td>35.15583</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>11.65902</td>
<td>11.09790</td>
</tr>
<tr>
<td><strong>Toy Wiz</strong></td>
<td>Mean</td>
<td>31.46890</td>
<td>39.32244</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>12.95802</td>
<td>10.38350</td>
</tr>
<tr>
<td><strong>Discount Anime Toys</strong></td>
<td>Mean</td>
<td>46.46684</td>
<td>50.89333</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>10.19761</td>
<td>10.13599</td>
</tr>
<tr>
<td><strong>Imperial Outpost Toys</strong></td>
<td>Mean</td>
<td>24.37095</td>
<td>24.37095</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>5.920103</td>
<td>5.920103</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>Mean</td>
<td>29.15503</td>
<td>33.84837</td>
</tr>
<tr>
<td></td>
<td>Std. Dev.</td>
<td>15.48063</td>
<td>16.35790</td>
</tr>
</tbody>
</table>
Figure 4

Toys R Us

Figure 5

Walmart
Figure 6

eToys

Figure 7

Kimmy Shop
Figure 8

Imperial Outpost Toys

Figure 9

Digitech
Figure 10

Dragostand Bakugan

Figure 11

Superhero Toys
Figure 12
Wall of Fame

Figure 13
Virtual King
Figure 14

Cozcorp

Figure 15

Toy Store Inc
Figure 16
Toy Wiz

Figure 17
Discount Anime
### Table II
Ebay, Total, Pre, and Post-Christmas Cumulative Statistics

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Pre-Christmas</th>
<th>Post-Christmas</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Final Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Auctions) Mean</td>
<td>25.32985</td>
<td>26.13453</td>
<td>13.64278</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.093804</td>
<td>8.685723</td>
<td>6.608313</td>
</tr>
<tr>
<td>N.o.bs</td>
<td>594</td>
<td>556</td>
<td>36</td>
</tr>
<tr>
<td><strong>Final Full Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Auctions) Mean</td>
<td>30.39039</td>
<td>31.21919</td>
<td>18.39333</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.323743</td>
<td>8.888276</td>
<td>7.042434</td>
</tr>
<tr>
<td>N.o.bs</td>
<td>594</td>
<td>556</td>
<td>36</td>
</tr>
<tr>
<td><strong>Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Buy it Now) Mean</td>
<td>27.44446</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.224412</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N.o.bs</td>
<td>65</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Full Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Buy it Now) Mean</td>
<td>30.60375</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.206060</td>
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</tr>
<tr>
<td>N.o.bs</td>
<td>65</td>
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<td></td>
</tr>
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</table>

### Table III
Weekend/Weekday Ebay Final Auction Prices

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Weekend</th>
<th>Weekday</th>
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<tbody>
<tr>
<td><strong>Final Price</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(Auctions) Mean</td>
<td>25.32985</td>
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<td>26.29640</td>
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<tr>
<td>Std. Dev.</td>
<td>9.093804</td>
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<td>8.806487</td>
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<td>N.o.bs</td>
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<td>347</td>
</tr>
<tr>
<td><strong>Final Full Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Auctions) Mean</td>
<td>30.39039</td>
<td>29.01500</td>
<td>31.36545</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.323743</td>
<td>9.777578</td>
<td>8.873930</td>
</tr>
<tr>
<td>N.o.bs</td>
<td>594</td>
<td>247</td>
<td>347</td>
</tr>
<tr>
<td><strong>Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Buy it Now) Mean</td>
<td>27.44446</td>
<td>29.25036</td>
<td>26.07784</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>9.224412</td>
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<tr>
<td>N.o.bs</td>
<td>65</td>
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<td>37</td>
</tr>
<tr>
<td><strong>Full Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Buy it Now) Mean</td>
<td>30.60375</td>
<td>32.96630</td>
<td>28.87973</td>
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<td>Std. Dev.</td>
<td>9.206060</td>
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</tr>
<tr>
<td>N.o.bs</td>
<td>65</td>
<td>27</td>
<td>37</td>
</tr>
<tr>
<td>Toy Store</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>-----------</td>
<td>------</td>
<td>-----------</td>
<td>------</td>
</tr>
<tr>
<td>Toys “R” Us</td>
<td>9.990000</td>
<td>0.000000</td>
<td>9.990000</td>
</tr>
<tr>
<td>Walmart</td>
<td>8.000000</td>
<td>0.000000</td>
<td>8.000000</td>
</tr>
<tr>
<td>Digitech</td>
<td>43.62461</td>
<td>16.64433</td>
<td>43.46094</td>
</tr>
<tr>
<td>Virtual King</td>
<td>37.62158</td>
<td>13.20287</td>
<td>36.86500</td>
</tr>
<tr>
<td>Cozcorp</td>
<td>23.77961</td>
<td>10.11902</td>
<td>23.54531</td>
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<tr>
<td>Toy Store Inc.</td>
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<td>11.65902</td>
<td>28.92750</td>
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<td>45.73625</td>
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<td>5.920103</td>
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<tr>
<td>Total</td>
<td>29.15503</td>
<td>15.48063</td>
<td>28.81047</td>
</tr>
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</table>
Figure 19
Results of EViews Full Price Regressed on Dummies for Days of the Week

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>MON</td>
<td>31.74957</td>
<td>1.108712</td>
<td>28.63644</td>
<td>0.0000</td>
</tr>
<tr>
<td>TUE</td>
<td>31.14234</td>
<td>1.057116</td>
<td>29.45973</td>
<td>0.0000</td>
</tr>
<tr>
<td>WED</td>
<td>32.08119</td>
<td>1.012111</td>
<td>31.69730</td>
<td>0.0000</td>
</tr>
<tr>
<td>THU</td>
<td>30.76345</td>
<td>0.861269</td>
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<td>0.0000</td>
</tr>
<tr>
<td>FRI</td>
<td>30.08244</td>
<td>1.050317</td>
<td>28.64128</td>
<td>0.0000</td>
</tr>
<tr>
<td>SAT</td>
<td>28.19900</td>
<td>1.037105</td>
<td>27.19010</td>
<td>0.0000</td>
</tr>
<tr>
<td>SUN</td>
<td>28.81068</td>
<td>0.988841</td>
<td>29.13581</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared      0.020214  Mean dependent var 30.39039
Adjusted R-squared 0.010182  S.D. dependent var 9.323743
S.E. of regression 9.276152  Akaike info criterion 7.304505
Sum squared resid 50423.54  Schwarz criterion 7.356269
Log likelihood -2158.786  Durbin-Watson stat 0.402591

Figure 20
Difference Between Coefficient of Day of the Week Dummies and Full Price Sample Mean (eBay)
**Figure 21**
Cumulative Price Change by Day of the Week for the 14 Online Retailers over the Entire Sample Period

**Figure 22**
Full Price Regressed on Dummy Variables for Each Day of the Week
Figure 23
Difference Between Coefficient of Day of the Week Dummies and Price Sample Mean for 9 retailers (excluding, Toys "R' Us, eToys, Walmart, KimmyShop, and Imperial Outpost Toys)

Figure 24
Weekly Percent of Auction Listings that Received at Least One Bid
Figure 25
Number of Bids Per Auction Over Time

Figure 26
Daily Average Full Price
### Figure 27
EViews OLS Regression Results of the Number of Bids Per Auction Regressed on Peak Demand Dummy and Full Starting Price

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FULLSTARTINGPRICE</td>
<td>-0.396889</td>
<td>0.025123</td>
<td>-15.79763</td>
<td>0.0000</td>
</tr>
<tr>
<td>DT</td>
<td>4.314007</td>
<td>0.425983</td>
<td>10.12718</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>14.44341</td>
<td>0.383551</td>
<td>37.65703</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| R-squared          | 0.349479    | Mean dependent var | 11.15278   |
| Adjusted R-squared | 0.347209    | S.D. dependent var  | 6.042538   |
| S.E. of regression | 4.882099    | Akaike info criterion | 6.014222  |
| Sum squared resid  | 136573.9    | Schwarz criterion   | 6.036910   |
| Log likelihood     | -1729.096   | F-statistic         | 153.9164   |
| Durbin-Watson stat | 1.467747    | Prob(F-statistic)   | 0.000000   |

### Figure 28
EViews OLS Regression Results of the Coefficient of Variation Regressed on Peak Demand Dummy

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>-0.035742</td>
<td>0.020264</td>
<td>-1.763809</td>
<td>0.0835</td>
</tr>
<tr>
<td>C</td>
<td>0.147647</td>
<td>0.012522</td>
<td>11.79141</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| R-squared              | 0.055444    | Mean dependent var | 0.134000   |
| Adjusted R-squared     | 0.037622    | S.D. dependent var  | 0.074426   |
| S.E. of regression     | 0.073013    | Akaike info criterion | -2.360680 |
| Sum squared resid      | 0.282536    | Schwarz criterion   | -2.287686  |
| Log likelihood         | 66.91869    | F-statistic         | 3.111023   |
| Durbin-Watson stat     | 1.421918    | Prob(F-statistic)   | 0.083528   |
Figure 29
EViews GLS Regression Results of the Coefficient of Variation Regressed on Peak Demand Dummy

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>-0.042175</td>
<td>0.022081</td>
<td>-1.910011</td>
<td>0.0621</td>
</tr>
<tr>
<td>C</td>
<td>0.154422</td>
<td>0.014376</td>
<td>10.74150</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.048472</td>
<td>0.206887</td>
<td>0.234293</td>
<td>0.8158</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.078047</td>
<td></td>
<td></td>
<td>0.136667</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.039632</td>
<td>S.D. dependent var</td>
<td>0.075410</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.073901</td>
<td>Akaike info criterion</td>
<td>-2.315171</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.262142</td>
<td>Schwarz criterion</td>
<td>-2.201534</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>62.03685</td>
<td>F-statistic</td>
<td>2.031699</td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson stat</td>
<td>1.076327</td>
<td>Prob(F-statistic)</td>
<td>0.142236</td>
<td></td>
</tr>
</tbody>
</table>

Inverted AR Roots: 0.05

Figure 30
Weekly Average Full Price and Coefficient of Variation
Table V
Week by Week (Monday-Sunday) Statistics (Full Price)

<table>
<thead>
<tr>
<th></th>
<th>Avg Full Price</th>
<th>Max</th>
<th>Min</th>
<th>StDev</th>
<th>StDev/Avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oct28-Nov1</td>
<td>23.08</td>
<td>27</td>
<td>16.5</td>
<td>2.643673</td>
<td>0.114544</td>
</tr>
<tr>
<td>Nov2-Nov8</td>
<td>24.48</td>
<td>52.95</td>
<td>18</td>
<td>5.119838</td>
<td>0.209144</td>
</tr>
<tr>
<td>Nov9-Nov15</td>
<td>35.49</td>
<td>50.95</td>
<td>22.24</td>
<td>5.70145</td>
<td>0.160649</td>
</tr>
<tr>
<td>Nov16-Nov22</td>
<td>38.54</td>
<td>52.95</td>
<td>22.75</td>
<td>5.725024</td>
<td>0.148548</td>
</tr>
<tr>
<td>Nov23-Nov29</td>
<td>40.54</td>
<td>51.17</td>
<td>31.5</td>
<td>4.449776</td>
<td>0.109763</td>
</tr>
<tr>
<td>Nov30-Dec6</td>
<td>34.61</td>
<td>47.95</td>
<td>22.5</td>
<td>6.058628</td>
<td>0.175054</td>
</tr>
<tr>
<td>Dec7-Dec13</td>
<td>26.57</td>
<td>40.7</td>
<td>17.5</td>
<td>4.592126</td>
<td>0.172831</td>
</tr>
<tr>
<td>Dec14-Dec20</td>
<td>19.45</td>
<td>27.95</td>
<td>12.5</td>
<td>4.073469</td>
<td>0.209433</td>
</tr>
<tr>
<td>Dec21-Dec27</td>
<td>18.21</td>
<td>21.45</td>
<td>14.94</td>
<td>2.411363</td>
<td>0.13242</td>
</tr>
<tr>
<td>Dec28-Jan3</td>
<td>19.29</td>
<td>49.98</td>
<td>13.24</td>
<td>9.49855</td>
<td>0.492408</td>
</tr>
</tbody>
</table>

Figure 31
EViews Regression Results of the Coefficient of Variation Regressed on Weekend Dummy
Works Cited


