Cannibalization within B2B Secondary Markets for IT: Evidence from a Field Experiment

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1 Introduction

It is generally accepted that the pace of new product development and introduction of new products in the IT sector has accelerated in the last 20 years. Researchers have referred to this phenomenon as clockspeed (Mendelson and Pillai 1999, Carrillo 2005), i.e. the speed with which products, services and organizational dynamics within the industry change. Rapid clockspeed in the IT industry has also been associated with a faster observed rate of new product development (Souza et al. 2004), requiring faster organizational changes by IT buyers (Nadkarni et al. 2007), and market volatility in the long run (McAfee and Brynjolfsson 2008). A direct consequence of this increased clockspeed is that multiple generations of technology products are typically present in the marketplace at any given time. For instance, when a new iPhone is released, there is also a concurrent rush for the sale of used iPhones of the previous generation in the marketplace[1]. Similarly, in the IT infrastructure market, the rapid generation of new products and the increased durability of older-generation equipment ensures that these older products remain around in the marketplace, even after the introduction of the newest products[2].

A natural question is what becomes of used IT equipment, such as computers, iPhones and iPads, when consumers switch to new ones. Scholars in the area of reverse logistics suggest multiple approaches for handling old IT equipment (Kumar and Putnam 2008). First, there is a possibility of take-back programs offered by the original equipment manufacturers (OEM), whereby the manufacturer takes back the old equipment, refurbishes and resells (Guide and Wassenhove 2001) or finds alternative ways to dispose the components through recycling. Second, the consumer has the option of "throwing away the old equipment, essentially creating e-waste (Robinson 2009), defined as products such as mobile phones, computers and peripheral equipment in landfills. Clearly, there is much cause for concern as e-waste grows, especially as product life-cycles shorten and the digital divide is bridged (Oteng-Ababio 2010). It is estimated that nearly 400 million electronic items end up in landfills every year. The third option, arguably preferred to the first two since it requires and incurs minimal additional cost, is the creation of secondary markets for these goods, where

[1] http://fortune.com/2014/08/27/with-two-weeks-to-go-used-iphones-flood-the-market/

[2] http://searchitchannel.techtarget.com/feature/Secondary-market-resellers-thrive-in-the-tech-industry

sellers of out-of-date or lightly used durable items like computers and tablets PCs can transact with buyers interested in these products at discounted prices (Kumar and Putnam 2008), without needing to alter the state/quality of the product. These markets form the specific focus of the research presented in this paper.

One of the primary research questions that have been addressed at secondary markets pertain to the effects that these markets have on the demand for new products, i.e. in the primary market. Since most IT products tend to be durable goods (Waldman 2003), there is always a threat of cannibalization of new sales by products in the secondary markets (Guide and Li 2010). The potential for such cannibalization influences many decisions taken by firms in the primary market, such as pricing, market entry and planned obsolescence (Ellison and Fudenberg 2000). The Internet has allowed the introduction of electronic market exchanges that have enhanced the interdependencies that exist between primary and secondary markets (Arunkundram and Sundararajan 1998, Lee and Whang 2002), even for non-IT products (Ghose et al. 2005).

A common question addressed in the cannibalization literature pertains to how the original manufacturer (OEM) should choose to price or position new generation products when the older generation product is still available in the secondary market. This question is raised most often in the context of understanding cross-market cannibalization, i.e. the extent to which products in the secondary market cause demand in the primary market to suffer (Moorthy and Png 1992). More recently, researchers have ventured to ask how the presence of remanufactured products in the secondary market impact the perceived value of the primary market goods (Agarwal et al. 2014).

Much of this research has studied the dynamics at the interface of the primary and secondary markets. However, when viewed together with increased clockspeed in the IT industry and the increased value and durability of IT equipment, a different form of cannibalization has emerged as relevant for study: the potential for cannibalization within the IT secondary market itself, across generations of products that are sold *concurrently* in the secondary market. Hence, the increasing numbers of products from preceding generations present in the marketplace, whether unused or refurbished, raise questions of a familiar nature but with a new twist.

Most of these products from preceding generations are sold on secondary markets, where sellers use multiple mechanisms to sell out-of-date or slightly used durables like computers, servers and tablets (Kumar and Putnam 2008). Secondary markets have always existed for products like financial instruments, real estate and durable goods like automobiles (Hendel and Lizzeri 1999; Esteban and Shum 2007). However, the growth of a viable secondary market for IT products is a relatively recent phenomenon and has emerged from the move towards to market exchanges that were observed during the Internet boom (Lee and Whang 2002). While hard data on the IT secondary market is high to come by, given the various markets and forms in which IT equipment is resold, anecdotal evidence suggests that the size of the IT secondary market in 2012 was approximately $300 Billion The source for this volume comes from multiple sources retail buyback programs[3], product returns[4], and firm replenishment cycles. Firms that host these secondary markets include familiar entities such as Best Buy, Amazon and eBay as well as others specializing in providing online platforms, such as Genco[5], LSI[6] and MarkITx[7].

This paper is our attempt to bring attention to this secondary market activity, highlight the challenges of market design therein, and provide some preliminary results. In the work reported here, we focus on the B2B secondary market for IT products. In addition, we focus attention on B2B *auctions* for IT equipment. Auctions have long been associated with secondary markets as a way to efficiently allocate products to those with the highest valuations (Lee and Whang 2002) and represent a large proportion of how sales in secondary markets are organized. Within this segment of the market, our objective is to understand the drivers of prices for B2B auctions of IT equipment.

We report on a unique opportunity for a field experiment that was conducted through the cooperation of a large secondary markets auctioneers for IT equipment in the United States. With the specific intention of understanding the effects of cannibalization within different generations of a similar product in the secondary markets, the research site allowed us to conduct a field experiment on their auction platform for one specific and well-understood product category –iPad tablets. As part of the experiment, over 600 pallets of second-generation and third-generation iPads (iPad2, iPad3) were made available to us, representing a total retail value of over $1 Million. Cannibalization in the context of auctions is captured through the concept of cross-price elasticity of demand (Guide and Li 2010, Ghose et al. 2006). Therefore, to assess the effects of cannibalization within one category of products, we exogenously manipulate the auction starting prices of specific pallets of products and analyze the resulting final prices on products in adjacent markets, where adjacency is based either on generation or quality of the products. By manipulating three such adjacent markets, we are able to provide estimates of cross-price elasticity within secondary markets for IT products, complementing existing work that only addresses primary versus secondary markets. In

[3]http://appleinsider.com/articles/13/11/01/how-and-where-to-trade-in-your-old-ipad-for-the-most-cash-or-store-credit
[4]http://www.skipmcgrath.com/articles/ebay-secondary-surplus-liquidation-market.shtml
[5]http://www.genco.com/Reverse-Logistics/reverse-logistics.php
[6]http://www.liquidityservicesinc.com/
[7]https://www.markitx.com/

addition, we contribute to a more nuanced understanding of cannibalization in the auction setting, rather than in posted price settings where cross-price elasticity can be more easily gauged (Ghose et al. 2006). In auction settings, cannibalization can manifest in two ways – the number of bidders in an auction, and the final willingness-to-pay on specific auctions. Using an experimental setting that offers clean identification, and using professional bidders as subjects, we provide evidence of cannibalization effects influencing bidders on an auction as well as the final prices that obtain.

2 Cannibalization within Secondary Markets

In a typical B2B auction, a lot represents a pallet of IT equipment worth several thousand dollars. Sellers acquire these pallets from retailers or large firms at discounted prices and place them on online auction platforms for bids. They have little control over their incoming inventory since these are decided by the dynamics of the primary market and the equipment replenishment cycles within firms (Thibodeau 2013). Therefore, as and when pallets of equipment are made available to the seller, they are posted on the online marketplace. Bidders on these platforms are themselves resellers, e.g. flea market vendors, wholesale liquidators, eBay power sellers and assorted mom and pop stores who vary greatly in their bidding activity and buying volumes on the auction sites (Pilehvar et al. 2013). As resellers, therefore, bidders have to be aware of the prices that these pallets will fetch in their destination market, which are often either in the B2C market or through flea markets.

Due to the nature of secondary market, used products in secondary markets can arrive to wholesale liquidators in a range of states of quality , from salvage condition to light-used/excellent quality. It is generally accepted that the highest profit potential resides with the newest (latest) generation, and that the profit potential quickly diminishes as the generations become older and products are of lower quality. With fast liquidation a critical part of their daily business model, wholesale liquidators often run several auctions for identical and comparable products, whereby comparable products differ only according to quality condition or models of the product (vertically differentiated products). Although, this practice can increase the speed of the liquidation, its net effect on the profits of individual product sales is unclear: Posting several auctions for comparable products can depress overall profits by facilitating cannablization, e,g,, offering bidders an opportunity to substitute bids on higher end products for lower bids on auctions of lower end products. Further complicating the market dynamics is the price revelation process that is inherent in auctions the buyer does not dictate a selling price but rather sets the tone for the auction via her starting price and then renders control over to the competitive forces of the market to determine the final price.

In such an auction environment, one important and open question to ask is how a seller manage the posting of overlapping generations/products on an auction site, so that she auctions off the right mix of products at the right starting price. While previous literature has considered the timing and pricing of new generations of products on existing generations, the literature has not raised its gaze to see further down the product line and evaluate the rippling effect that may occur across older generations coexisting and actively traded in secondary markets. That is, while the the interplay of posted prices between the latest and next-latest product generations has been studied the field has generally ignored the continuing market forces that connect successively older generations of IT technology that are still useful and actively being traded on B2B and B2C platforms.

Since multiple generations of products, with heterogeneous quality, can be sold concurrently in these markets, identifying cross-price elasticities, if any, is critical in ensuring the efficiency of these markets. Additionally, since the auction mechanism is used primarily in these markets, the potential for cannibalization is driven by an interaction of starting prices and prices observed from other similar products in the market (Pilehvar et al. 2013). We briefly describe how starting prices may influence cannibalization in these settings next.

Significant research has established that starting prices are critical in influencing bidder dynamics and the final prices that result in online auctions (Ariely and Simonson 2003, Bajari and Hortacsu 2003). Starting or reserve prices serve as quality signals to bidders, while also influencing the number of bidders who choose to enter the auction (Ku et al. 2006, Simonsohn and Ariely 2008). By manipulating the starting price for a lot, sellers can thus influence the number of bidders as well as, in the case of common or affiliate value auctions, the willingness to pay for each bidder (Pilehvar et al. 2013, Kamins et al. 2004). In addition to starting prices on the focal auction, prior work shows that it is possible to influence bidding behavior by focusing the bidders attention on adjacent auctions (Dholakia and Simonson 2005), through the use of advertised prices that are influential (Wolk and Spann 2008) and through current prices observed on other auctions that are deemed comparable and similar (Pilehvar et al. 2013). Indeed, Nunes and Boatwright (2004) show that incidental prices on unrelated products may also serve to influence the bidders willingness to pay.

The theoretical mechanism through which these effects manifest are reference prices, i.e. the standards against which the purchase price of a product is judged (Mazumdar et al. 2005). Within this literature, consumers make decisions by comparing posted prices to a set of reference prices that provide reasonable anchors for valuation (Yadav and Seider 1998). These reference prices may be internal (based on prices observed historically), external (such as those from adjacent products) or advertised prices (Adaval and Monroe 2002). Within the auction setting, therefore, starting prices serve as important price anchors (Haubl and Popkowski Leszczyc 2003), while prices on adjacent or proximal lots serve as external reference prices (Wolk and Spann 2008). In the context of secondary markets, where products in the auction often have uncertain quality and incomplete product descriptions, the starting price anchors set by sellers become strategic variables by which sellers can influence the focal auction. In addition, by manipulating starting prices suitably, the seller can either enhance or reduce the extent to which adjacent products appear to be substitutes for the focal product, thereby influencing the extent to which demand substitution may occur, hence leading to cannibalization. Thus, setting starting prices strategically can influence demand for the focal product, through own-price elasticity of demand, as well as demand for similar but adjacent products, through cross-price elasticity of demand.

In the field experiment described in the next section, we build on this logic to create the experimental treatments that lead to a higher or lower occurrence of observed cannibalization on the auction platform. We first argue that cannibalization on online auction platforms occur in two ways. First, auctions that are cannibalized by other auctions on similar products experience lower bidder entry, leading to a lower number of bidders, ceteris paribus. Second, by providing suitable reference price signals through the manipulation of starting prices, bidder willingness to pay can also be influenced, consistent with prior research (Guide and Li 2010). In order to identify these two effects, using a field study we randomly manipulate starting prices for the focal product for each experimental day on the platform. Second, we exogenously manipulate starting prices for the adjacent products posted on the platform simultaneously. Using these two treatments, and by appropriately accounting for other influences on bidders, we can identify the effects of starting prices on number of bidders and final prices that are obtained on the focal auction as well as on adjacent auctions.

We conduct our field experiments in two stages. In the first stage, we replicate current work from the literature by holding the high-end, high-quality product constant while manipulating starting prices on two adjacent but lower-quality products. In the second stage, we study the effect of the treatments on the middle product, which is sandwiched between the stable high-end product and a moving lower-quality product. Across both sets of manipulations, our results show that starting prices influence the extent to which there is demand substitution, and hence cannibalization, occurring on the platform, influencing both bidder entry as well as final prices. We describe the experimental setting in detail next.

3 Field Experiment

We report here on the results of a field experiment that we ran in November 2012- December 2012 on the auction site of one of the nations largest online auction wholesale liquidation sites. The design of this field experiment was directly aimed at understanding how (i) the starting price of the auction, and (ii) the prices on other generations/quality, interacts to impact an auctions final price.

The auction and bidding formats are almost identical to that found on eBay: Once a bid has been submitted, the auction tool serves as a proxy bidder and updates the bid on behalf of the bidder in the minimum bid increment necessary for that bidder to maintain a winning bid position, or until the bidder's submitted bid level has been reached. When the auction ends, the bidder with the highest bid wins the auction and pays the second-highest bid plus the minimum bid increment.

In order to reduce unobservable heterogeneity in the auction environment and to standardize the items for auction to the extent possible, we ran the field experiment on a set of electronic products that were well understood and clearly specifiable iPad tablets. We conducted the experiment on two sets of products - used 2^{nd} generation iPads (iPad2) and 3^{rd} generation iPads (iPad3). The experiment included 24 "days" of auctions excluding the holiday season, and consists of 800 successful auctions totaling over $1.2 million revenues. The pallet of goods in each auction in the sample consisted of a pallet of the same generation iPads, with the average size of 4.2 units (std. dev. = 1.2). In addition, for the iPad2 auctions, the products could be of two grades of quality: light-use and moderate-use (a lower quality level).

The quality grade and characteristics of the products are exogenously determined by the retailer upon receipt of the returned items and are not defined by the auction site. As part of the experimental design, we were allowed the opportunity to randomly set starting prices for each set of auctions, across generations and quality levels, on a given day (within acceptable ranges), thereby guaranteeing exogeneity of these parameters. Thus, the design of the experiment allows us to tease out the effects of varying starting prices on the recovery rates of auctions across the generational and quality dimensions. Of specific interest to the auction company was the impact of starting prices of 'lower-grade' products on 'higher-grade' ones. As was noted in the previous section, the highest profit potential resides with the newest (latest) generation, with profit potential quickly diminishing as the generations become older and products are of lower quality. For this reason, we are interested in understanding how starting prices on products on the lower end of the spectrum impact prices of new generation or higher quality products.

We synchronized the start of the auctions so as to have them simultaneously open each day, lasting approximately 2 calendar days each. To minimize the effects of simultaneous auctions that are not part of a cohort of auction starting prices conditions, each set of auctions began after the termination of the previous set of auctions, i.e. there was perfect overlap between auctions that started on the same day and zero overlap with auctions that started on other days as part of the experimental design. The starting prices of auction for each auction was fixed within a day and was recommended by the channel manager. Given the relative abundance of iPad2s in inventory compared to iPad3s, we were allowed to manipulate the starting price for iPad2s. Hence, for each of the 24 experimental "day", we determined the starting price for two sets of iPad products, iPad2/light-use ($iP2_L$) and iPad2/moderate-use ($iP2_M$). In consultation with channel managers, we identified a reasonable low and high starting price for $iP2_L$ and $iP2_M$: The low (high) starting price for $iP2_L$ were 55% (70%) of retail value ($399); the low (high) starting price for $iP2_M$ were 50% (65%) of retail value ($399). That is, for each day in our experiment, all $iP2_L$ auctions had the same starting price (either High or Low) and all $iP2_M$ auctions had the same starting price (either High or Low), All iPad3 auctions had a starting prices in the range of 66% of retail value. These experimental settings are shown in Figure 1.

4 Predictors and Empirical Analysis

Figure 1 illustrates the products considered within our experiment, with $iP2_M$ at the lowest end of the market and $iP3$ at the top of the market, with $iP2_L$ sandwiched in between. The four lines depict the four conditions within our experiment; the dollar figure quoted below each product category represents the starting price for the product-auction in that condition; the dollar figure above reflects the average final price for each product-auction. For example, in Scenario 1, the starting price for all $iP2_M$ ($iP2_L$) auctions was $200 ($220), while the average final price for these auctions was $290 ($300).

From Figure 1 we can glean that varying starting prices does appear to impact the final prices in the market. In particular, a higher starting price for $iP2_L$ appears to result in a higher $iP2_L$ final price. What is not immediately evident from this aggregate analysis is if there are any externalities between the starting prices of lower product categories on higher product categories. That is, does a higher $iP2_M$ price positively influence the final price for $iP2_L$ and possibly even $iP3$, which is

Figure 1: Starting and Average Final Prices in Field Experiment

further away on the product placement array. Similarly, does a higher $iP2_L$ starting price positively impact the final price of $iP3$?

Given the simple experimental setup, we use a series of linear regressions to test our hypotheses, with the unit of analysis being the auction. Since the auctions in our experimental design naturally fall into cohorts of similar starting prices, we control for this by including the "day" of the experiment in all of our analysis. We also include several control variables in our analysis, described below.

- Q: On the auction site, bidders are informed as to the total number of items in the pallet Q. There are typically 4-6 items in a pallet (see Table Summary Stats).

- $Starting\ Price_{IP2_x}$: Bidders can also see the starting price for each iPad category. Our experimental design was 2 (iPad 2 light-use starting price: High, Low) x 2 (iPad 2 moderate-use starting price: High, Low) where both starting prices were manipulated between auctions. $SP_{IP2_x} = 1$ denotes a High starting price, $x \in (\mathbf{L}ight - use, \mathbf{M}oderate - use)$. The posit that the starting prices may serve as external price references and hence influence the final prices in auctions.

- $Past\ Price_x$: In addition to the starting prices of currently open auctions, we define $Past\ Price_x$ to be the average price for $x \in (iP2_L, iP3)$ auctions closing the previous day. Prior work in B2C marketing has identified internal reference prices as influential determinants of a consumers willingness to pay for a product. An IRP is generally based on prices the consumer has observed in the past and is primarily self-generated from memory and dynamic. As new prices are observed and assimilated, the IRP is updated appropriately (Yadav and Seiders 1998). As such, we create a variable to track the average closing price of auctions for the same category.

- $Ratio\ iP2_L(Ratio\ iP3)$: The auction platform groups all iPads together in the same search category; hence a bidder wishing to purchase iPad2s was unable to refine his/her search beyond the general category of 'iPad. This platform design attribute implies that bidders were generally exposed to prices across all iPad categories, whether or not they were interested in them. So as to avoid having all the auctions close at the exact same time, auction designers typically staggered the closing of auctions in 5 minute increments. The assignment of closing times to pallets(auctions) was randomly generated; this generally resulted in bidders being exposed to the starting prices of all the iPad categories if they arrived at the start of the auctions. Furthermore, we learned that the default user setting for viewing auctions posted the 25 closest to finish auctions on the first page of a search. The variable $Ratio_{iP2_L}$ ($Ratio_{iP3}$) captures the fraction of $iP2_L$($iP3$) auctions in the 25 soonest to end auctions.

Note that since the $iP3$ prices are fixed during the duration of the experiment, they do not appear in any of the analyses. Given the presence of auctions of different categories of products, we conduct our analysis of final prices independently for each market: the summary statistics for $iP2_L$ and $iP3$ markets are shown in Tables 1 and 2 respectively.

Prior research indicates that auction final prices are strongly driven by the number of bidders who appear in the auction. Therefore, in trying to identify the effects of cannibalization here, we consider the effects of starting price settings on both the number of bidders in an auction and the resulting final price. Since the number of bidders appearing in an auction is not random but generated through a decision process, the coefficient associated with this variable in the FP analysis is likely to be biased due to endogeneity. Therefore, we need to instrument for this variable appropriately. We identify two possible instruments here for N: The first one is the relative proportion of iPad3 pallets that show up on the interface of the online auction when the user searches for auctions on iPads. Since the interface typically lists out pages of auctions in sets of 25 auctions sorted by those soonest to end (i.e. auctions closest to their ending time are listed earlier), the number of relevant auctions of iPad3 (iPad2s) that show up on this listing is likely to influence the choice of the bidder to enter that auction, thereby increasing the number of bidders in a focal auction. However, this variable is unlikely to systematically influence the final price or willingness to pay of the bidder for that particular pallet. Therefore, while prior research shows that bidders prefer to enter empty auctions or those with fewer bids, these do not influence the specific willingness to pay. This variable thus serves the purpose of an instrument, i.e. it is correlated with the endogenous variable (N) but uncorrelated with the dependent variable (Final Price).

Similarly, we use the auction closing hour as an instrument - here again, we argue that closing hour influences bidder entry (auctions closing in the evenings have different odds of bidder entry than auctions closing at noon) but should not affect willingness to pay. Using these two instruments for N, we estimate a two-stage least squares analysis, where equations for N and FP are estimated simultaneously. Note however that since our primary interest is in the effect of starting price variations of focal and adjacent markets on N and FP, and starting prices are randomly generated through the experiment, these coefficients are estimated without any bias.

Table 1: Summary statistics for $iP2_L$ auctions based on 308 observations

Variable	Mean	Std. Dev.	Min	Max
$FP(\$)$	\$1,352.89	\$165.81	\$609	\$2,076
N	2.765	0.685	2	6
Q	4.389	0.544	2	6
$Starting\ Price_{iP2_L}$	0.473	0.502	0	1
$Starting\ Price_{iP2_M}$	0.463	0.499	0	1
$Past\ Price_{iP2_L}$				
$Ratio_{iP2_L}$	0.436	0.075	0	1

Table 2: Summary statistics for $iP3$ auctions based on 225 observations

Variable	Mean	Std. Dev.	Min	Max
$FP(\$)$	\$1,637.56	\$243.39	\$780	\$2,453
N	2.485	0.768	1	5
Q	4.3	0.755	2	6
$Starting\ Price_{iP2_L}$	0.437	0.497	0	1
$Starting\ Price_{iP2_M}$	0.484	0.501	0	1
$Past\ Price_{iP3}$				
$Ratio_{iP3}$	0.445	0.161	0	1

5 Results

We present our 2SLS regression results in in Tables 3 - 6. To gain insight into the nature of cannibalization in these auctions, we conduct our analysis in two manners: We run 2SLS regression on the full dataset (in the columns labeled *All Scenarios*) , and then on each pair-wise scenario data (labeled accordingly). The pair-wise regression analysis allows us to highlight the impact of specific changes in starting price in a cleaner manner. For each set of data, we run 3 separate regressions for N and two for FP. In our regressions for N, we first start with a benchmark model (I), and then incrementally add $Past\ Prices_{iP3}$ (labeled II) and then $Ratio_{iP2_L}$ (labeled III). In the regressions for FP, we report both the benchmark (I) as well as the full regression (III). Given the relative consistency in the results across these two forms of analysis, we focus our discussion below on the pairwise regressions.

5.1 iP3

We begin by analyzing the $iP3$ market and the regressions for N. Recall that we were not able to manipulate the starting price for $iP3$ auctions.

Looking at Table 3, and examining the pairwise-scenarios comparisons, we see a clear pattern emerge. the number of bidders in $iP3$ auctions are generally unaffected by starting price changes in the lower product auctions provided that starting prices have a 'natural' ordering, i.e., $Starting\ Price_{iP2_M} < Starting\ Price_{iP2_L}$. When we create a market with 'unnaturally' ordered starting prices, we find that restoring the natural order of prices *does* cannibalize bidders from $iP3$; in the pairwise comparison of Scenarios 2-3, the coefficient for $Starting\ Price_{iP2_L}$ is negative, whereas the coefficient for $Starting\ Price_{iP2_M}$ is positive in Scenarios 1-3. We also find that the final prices of recently closed $iP3$ auctions ($Past\ Price_{iP3}$) has a positive effect on the number of bidders participating in $iP3$ auctions: the higher the past closing price, the higher the participation numbers.

Given their relative diminutive influence on bidder participation, it is possible that the final prices for $iP3$ auctions are equally impervious to reference price effects. Upon examination of Table 4 we find that this is not the case. We find that higher starting prices for either $iP2_M$ or $iP2_L$ does *increase* the final price of $iP3$ auctions. For example, in the comparison of Scenarios 1-4, if we start in Scenario 1, where both $iP2_M$ and $iP2_L$ have a low starting price, an increase in the starting price of $iP2_L$ results in approximately a \$9 increase in the final price of a $iP3$ auction. Similarly, in the comparison of Scenarios 2-4, if we start in Scenario 4, where $Starting\ Price_{iP2_M}$ is low and $Starting\ Price_{iP2_L}$ is high, increasing the starting price for $iP2_M$ yields approximating a \$7 increase in the final price of a $iP3$ auction. The positive evidence of external reference prices is intuitive, and consistent with previous work in this area (Nunes and Boatwright (2004) and Pilehvar et al. (2013)). We also find that the $Past\ Price_{iP3}$, while not statistically significant, has a positive coefficient.

5.2 $iP2_L$

The role of starting prices in cannibalization emerge when we examine the 'middle' product, $iP2_L$. In Table 5, we see that setting a higher starting price for $iP2_L$ yields a reduction in the number of bidders (evidenced by the negative coefficient for $Starting\ Price_{iP2_M} * Starting\ Price_{iP2_L}$) for Scenarios 1-2. This results is also evidenced in the columns associated with Scenarios 1-4 and Scenarios 2-3 by the negative coefficient for $Starting\ Price_{iP2_L}$ and Scenarios 2-4 by the negative (albeit statistically insignificant) sign for $Starting\ Price_{iP2_M}$. Interestingly, we find that creating an unnatural ordering where $iP2_L$ is perceived as cheaper that $iP2_M$ (Scenarios 1-3) results in an increase in the number of bidders in $iP2_L$ auctions.

The effect of starting prices on cannibalization in $iP2_L$ does not stop with its impact on N. As with $iP3$ auctions, we find that $iP2_L$ auctions are subject to external reference price influences. As reported in Table 6 We find that a high starting price for $iP2_L$ has a positive impact on its own final price, as evidenced by the positive coefficient for $Starting\ Price_{iP2_L}$ in for Scenario 1-4 and Scenario 2-3, and by the positive coefficient for $Starting\ Price_{iP2_M} * Starting\ Price_{iP2_L}$ in Scenarios 1-2. Therefore, an increase in the starting price of $iP2_L$ has two diametrically opposed influences on the final price of $iP2_L$ auctions: it reduces the number of bidders in $iP2_L$ auctions, which then have a direct negative economically significant on the final prices, but a higher $iP2_L$ starting price directly exerts a positive influence on the final prices via reference price influences.

Finally, as opposed to $iP3$ auctions, we find that the final prices of recently closed $iP2_L$ auctions ($Past\ Price_{iP2_L}$) has a positive effect on the final price of $iP2_L$ auctions, hence providing evidence for the positive role of internal reference prices.

Table 3: $iP3$ auctions: Full plus Pairwise Scenario Comparison for Predictor N

Predictor: N	All Scenarios			Scenario 1-2			Scenario 2-4		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Q	-0.1024	-0.1273	-0.1257	-0.2607**	-0.2789**	-0.3045**	0.1495	0.0700	0.0677
	(0.088)	(0.088)	(0.089)	(0.127)	(0.129)	(0.128)	(0.139)	(0.138)	(0.137)
$SP\ iP2_L$	-0.0254	-0.0658	-0.0603						
	(0.136)	(0.136)	(0.141)						
$SP\ iP2_M$	0.6482***	0.5988***	0.5988***				0.0817	0.0575	0.1678
	(0.133)	(0.134)	(0.134)				(0.133)	(0.129)	(0.148)
$SP\ iP2_M * SP\ iP2_L$	-0.6262***	-0.6052***	-0.6121***	0.0377	0.0231	0.0762			
	(0.212)	(0.210)	(0.216)	(0.119)	(0.121)	(0.122)			
$PP\ iP2_L$		0.0096**	0.0095**		0.0035	0.0051		0.0150***	0.0109*
		(0.004)	(0.004)		(0.004)	(0.004)		(0.005)	(0.006)
Ratio iP3			0.1002			-2.0356**			-1.7026
			(0.693)			(1.009)			(1.132)
End Time	-0.0351***	-0.0351***	-0.0351***	-0.0361***	-0.0362***	-0.0370***	-0.0159	-0.0148	-0.0192
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
Weekend Close	-0.0808	-0.1120	-0.1179	0.2749*	0.2298	0.2388	-0.3162	-0.2494	-0.3154
	(0.137)	(0.136)	(0.143)	(0.155)	(0.164)	(0.162)	(0.194)	(0.190)	(0.194)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.2861***	-0.1840	-0.2045	3.7763***	2.5510	2.6278*	2.4210***	-3.1712	-0.9006
	(0.489)	(1.655)	(1.664)	(0.653)	(1.578)	(1.559)	(0.779)	(2.119)	(2.591)
Observations	225	225	225	133	133	133	115	115	115
R-squared	0.302	0.318	0.318	0.231	0.236	0.261	0.244	0.297	0.312

Predictor: N	Scenario 1-4			Scenario 2-3			Scenario 1-3		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Q	-0.0599	-0.0820	-0.0960	0.1709	0.0914	0.1174	-0.1173	-0.1270	-0.1224
	(0.124)	(0.123)	(0.124)	(0.130)	(0.130)	(0.131)	(0.105)	(0.107)	(0.108)
$SP\ iP2_L$	-0.0084	-0.0621	-0.1598	-0.4556***	-0.4595***	-0.4533***			
	(0.130)	(0.131)	(0.162)	(0.140)	(0.136)	(0.136)			
$SP\ iP2_M$							0.6886***	0.6757***	0.6764***
							(0.120)	(0.123)	(0.123)
$SP\ iP2_M * SP\ iP2_L$									
$PP\ iP2_L$		0.0091**	0.0122**		0.0177***	0.0240***		0.0028	0.0018
		(0.005)	(0.005)		(0.007)	(0.008)		(0.005)	(0.006)
Ratio iP3			-1.2793			1.5263			0.4278
			(1.260)			(1.070)			(1.086)
End Time	-0.0137	-0.0131	-0.0149	-0.0574***	-0.0571***	-0.0549***	-0.0442***	-0.0442***	-0.0443***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Weekend Close	-0.1423	-0.1252	-0.0155	-0.1136	-0.2001	-0.1451	-0.0820	-0.0933	-0.1438
	(0.152)	(0.150)	(0.185)	(0.228)	(0.224)	(0.227)	(0.183)	(0.184)	(0.225)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.0193***	-0.2848	-1.0172	2.3586***	-4.1379	-7.5389**	3.4236***	2.4337	2.6142
	(0.639)	(1.767)	(1.909)	(0.859)	(2.576)	(3.500)	(0.566)	(1.879)	(1.940)
Observations	132	132	132	123	123	123	140	140	140
R-squared	0.083	0.113	0.120	0.403	0.438	0.448	0.384	0.385	0.386

Table 4: $iP3$ auctions: Full plus Pairwise Scenario Comparison for Predictor FP

Predictor: FP	All Scenarios		Scenario 1-2		Scenario 2-4		Scenario 1-4		Scenario 2-3		Scenario 1-3	
	I	**III**	**I**	**III**	**I**	**III**	**I**	**III**	**I**	**III**	**I**	**III**
N	17.8127***	15.1664***	32.2669***	33.9537***	17.7768*	8.8775	43.2724	12.2470	20.3435***	21.6404***	20.9732***	19.7664**
	(2.014)	(1.643)	(8.887)	(8.778)	(9.007)	(15.528)	(40.164)	(19.833)	(6.585)	(6.342)	(7.994)	(7.922)
Q	3.4094***	3.0077***	-6.0857	-6.6259	-25.5663***	-26.0104***	-14.3967***	-16.5789***	-7.9111**	-8.1685**	-2.7242	-3.5284
	(1.010)	(0.789)	(4.146)	(4.330)	(3.696)	(3.946)	(4.883)	(3.481)	(3.325)	(3.358)	(2.762)	(2.772)
$SP\ iP2_L$	9.7109***	4.8844***					4.8922	2.7381	8.2429*	8.8353*		
	(2.021)	(1.656)					(4.752)	(3.677)	(4.570)	(4.564)		
$SP\ iP2_M$	2.4745	0.4283			6.8699**	7.0470*					0.8002	0.7033
	(2.132)	-1.651			(3.359)	(3.654)					(6.157)	(6.030)
$SP\ iP2_M * SP\ iP2_L$	-3.6019	-0.7079	9.8352***	9.0477**								
	(2.934)	(2.278)	(3.382)	(3.493)								
$PP\ iP2_L$		0.5854***		0.1801		0.3452		0.2745		0.0148		0.1932
		(0.050)		(0.123)		(0.277)		(0.216)		(0.204)		(0.124)
Ratio iP3	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*
End Time	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*
Weekend Close	-0.0093	-2.3734*	-12.0273**	-14.7696***	-1.3962	-2.6110	-1.2111	-4.9432	-1.3002	-1.2512	-3.5358	-4.4313
	(1.833)	(1.434)	(4.948)	(5.103)	(5.519)	(6.396)	(7.779)	(4.570)	(5.607)	(5.857)	(4.618)	(4.578)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	240.4908***	71.2186***	287.5878***	219.3907***	416.7141***	307.4887***	300.5058***	286.4597***	328.1171***	320.6413***	307.4257***	241.3508***
	(8.530)	(14.243)	(32.542)	(48.185)	(25.868)	(78.944)	(112.992)	(46.536)	(22.792)	(72.938)	(25.395)	(47.859)
Observations	308	308	133	133	115	115	132	132	123	123	140	140
R-squared	0.434	0.659	0.765	0.755	0.820	0.792	0.618	0.811	0.800	0.794	0.823	0.830

Table 5: $iP2_L$ auctions: Full plus Pairwise Scenario Comparison for Predictor N

Predictor: N	All Scenarios			Scenario 1-2			Scenario 2-4		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Q	-0.1554**	-0.1546***	-0.1267**	-0.1374	-0.2283**	-0.2324**	-0.0031	-0.0527	-0.0846
	(0.060)	(0.059)	(0.054)	(0.106)	(0.106)	(0.098)	(0.083)	(0.081)	(0.079)
$SP\ iP2_L$	-0.3111**	-0.4001***	-0.1526						
	(0.122)	(0.123)	(0.116)						
$SP\ iP2_M$	0.3064**	0.2438*	0.2038*				-0.1248	-0.0786	-0.0836
	(0.128)	(0.127)	(0.116)				(0.107)	(0.103)	(0.100)
$SP\ iP2_M * SP\ iP2_L$	-0.2870	-0.2045	-0.2658	-0.3115**	-0.3076**	-0.2091*			
	(0.181)	(0.179)	(0.163)	(0.128)	(0.124)	(0.117)			
$PP\ iP2_L$		0.0127***	0.0089***		0.0189***	0.0096*		0.0191***	0.0170***
		(0.004)	(0.003)		(0.006)	(0.005)		(0.005)	(0.005)
Ratio iP2			-3.4036***			-2.9774***			-2.1796***
			(0.431)			(0.574)			(0.651)
End Time	-0.0238**	-0.0248**	-0.0263***	-0.0073	-0.0096	-0.0122	-0.0222*	-0.0209*	-0.0246**
	(0.010)	(0.010)	(0.009)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Weekend Close	0.0984	0.0439	-0.2986***	0.0874	-0.1668	-0.2691	-0.3109*	-0.3995***	-0.3336**
	(0.116)	(0.115)	(0.113)	(0.164)	(0.175)	(0.163)	(0.158)	(0.153)	(0.149)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.9352***	0.0676	2.6422**	3.6739***	-1.5343	2.5145	3.0529***	-2.6323*	-1.0037
	(0.301)	(1.137)	(1.085)	(0.480)	(1.599)	(1.674)	(0.424)	(1.542)	(1.569)
Observations	308	308	308	164	164	164	157	157	157
R-squared	0.195	0.228	0.362	0.095	0.157	0.282	0.132	0.210	0.266

Predictor: N	Scenario 1-4			Scenario 2-3			Scenario 1-3		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Q	-0.1827**	-0.2386***	-0.1395	-0.1517*	-0.1255	-0.1356*	-0.1361*	-0.1366*	-0.0823
	(0.088)	(0.089)	(0.091)	(0.082)	(0.081)	(0.069)	(0.079)	(0.079)	(0.078)
$SP\ iP2_L$	-0.2204*	-0.3426***	-0.0142	-0.7086***	-0.7057***	-0.4709***			
	(0.120)	(0.128)	(0.156)	(0.138)	(0.135)	(0.120)			
$SP\ iP2_M$							0.3861***	0.3981***	0.4279***
							(0.128)	(0.131)	(0.128)
$SP\ iP2_M * SP\ iP2_L$									
$PP\ iP2_L$		0.0137**	0.0054		0.0138***	0.0128***		-0.0019	-0.0027
		(0.006)	(0.006)		(0.005)	(0.004)		(0.004)	(0.004)
Ratio iP2			-3.4977***			-3.3023***			-2.4771***
			(1.001)			(0.460)			(0.784)
End Time	-0.0413***	-0.0403***	-0.0362***	0.0053	0.0002	-0.0089	-0.0212*	-0.0208*	-0.0218*
	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
Weekend Close	-0.1283	-0.1039	-0.4922***	1.0468***	0.9424***	0.5593***	0.8648***	0.8826***	0.2898
	(0.135)	(0.133)	(0.170)	(0.235)	(0.233)	(0.206)	(0.172)	(0.177)	(0.255)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	4.4887***	0.5829	4.2031**	2.5950***	-1.7791	0.0523	4.1553***	4.7460***	5.9345***
	(0.430)	(1.645)	(1.897)	(0.458)	(1.678)	(1.454)	(0.363)	(1.396)	(1.405)
Observations	165	165	165	143	143	143	151	151	151
R-squared	0.211	0.240	0.295	0.314	0.349	0.530	0.455	0.456	0.492

Table 6: $iP2_L$ auctions: Full plus Pairwise Scenario Comparison for Predictor FP

Predictor: FP	All Scenarios		Scenario 1-2		Scenario 2-4		Scenario 1-4		Scenario 2-3		Scenario 1-3	
	I	**III**	**I**	**III**	**I**	**III**	**I**	**III**	**I**	**III**	**I**	**III**
N	17.8127***	15.1664***	17.2828***	11.4268***	16.2443***	11.8591***	18.0542***	11.8291***	19.3607***	18.4781***	15.1560***	14.9626***
	(2.014)	(1.643)	(1.999)	(1.753)	(3.651)	(2.541)	(2.390)	(1.810)	(3.169)	(2.778)	(5.687)	(4.910)
Q	3.4094***	3.0077***	5.7871***	2.1196**	4.3047***	2.3904***	6.8752***	3.4285***	1.7559	2.6357*	3.6320**	3.8014**
	(1.010)	(0.789)	(1.195)	(0.991)	(1.205)	(0.770)	(1.168)	(0.871)	(1.645)	(1.413)	(1.724)	(1.493)
$SP\ iP2_L$	9.7109***	4.8844***					10.8245***	4.6218***	8.2689**	7.6179**		
	(2.021)	(1.656)					(1.538)	(1.215)	(3.467)	(3.014)		
$SP\ iP2_M$	2.4745	0.4283			-1.4489	-0.2968					4.4996	1.3991
	(2.132)	-1.651			(1.632)	(0.990)					(3.410)	(3.033)
$SP\ iP2_M * SP\ iP2_L$	-3.6019	-0.7079	5.6751***	3.9113***								
	(2.934)	(2.278)	(1.545)	(1.191)								
$PP\ iP2_L$		0.5854***		0.5744***		0.7207***		0.5721***		0.5658***		0.5212***
		(0.050)		(0.057)		(0.068)		(0.054)		(0.094)		(0.076)
Ratio iP2	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*
End Time	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*	*instrument*
Weekend Close	-0.0093	-2.3734*	4.1508**	-3.0493**	-0.6781	-5.4677***	-2.6054	-2.7986**	-5.6399	-8.7474*	6.2236	1.5993
	(1.833)	(1.434)	(1.808)	(1.518)	(2.598)	(1.796)	(1.725)	(1.164)	(5.585)	(4.731)	(6.052)	(5.367)
Dummies(location+time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	240.4908***	71.2186***	225.9369***	87.9825***	249.1526***	47.9752***	221.3657***	83.5480***	255.6940***	75.6855***	251.0010***	89.2163***
	(8.530)	(14.243)	(8.815)	(13.895)	(12.038)	(16.083)	(10.585)	(13.880)	(11.564)	(28.959)	(22.701)	(33.012)
Observations	308	308	164	164	157	157	165	165	143	143	151	151
R-squared	0.434	0.659	0.683	0.823	0.561	0.834	0.568	0.805	0.383	0.543	0.418	0.568

6 Managerial Insights

In the Business-to-Business (B2B) secondary market, large retailers (such as Sears, Target, Walmart, etc.) can liquidate and business buyers (e.g., off-price retailers, eBay power sellers, etc.) can purchase excess and returned inventory at discounted prices. Many retailers have shifted the responsibility of disposing of this leftover inventory to large wholesale liquidators who commonly use B2B auctions as the preferred sale mechanism.

The work presented here makes three significant contributions to the literature. First, we focus attention on the issue of secondary markets for IT goods, a more sustainable solution to the increasingly pressing issue of e-waste and sustainable IT procurement. Efficient and workable secondary markets form a core part of the sustainable design paradigm for IT equipment. Second, we extend prior work in online auctions, observed almost exclusively in the B2C market (Bapna et al. 2003; Pinker et al. 2003) to the B2B sector for IT goods. Since B2B auctions, especially in the secondary market, are prone to significant quality uncertainty, our analysis here identifies and builds on prior work on starting prices and prices in adjacent markets that have been used to predict auction dynamics within the literature (Bajari and Hortacsu 2003). More to the point, we are able to separate the effects of starting prices from adjacent markets by clearly differentiating the higher-quality market from the lower-quality market in a marketplace with similar vertically differentiated products.

Finally, we add to the literature on reference prices within auction environments, where prior work has studied the influence of external reference prices observed on the auction platform on bidding behavior (Dholakia et al. 2002; Kamins et al. 2004). We show, albeit in the B2B context, that prices in adjacent markets as well as prices from previously posted auctions continue to influence final prices even in the presence of well-specified products in the secondary market. Thus, our analysis provides an extremely clean estimation of the effect of starting prices across the marketplace on final prices where there is still some residual uncertainty in the product, unlike in the primary market where there is relatively low variation around the quality of the product. We are also able to provide these estimates under three conditions that are rarely observed together in the empirical auctions literature. First, we use data from actual bidders who are professionals in the field, thereby limiting any concerns about generalizability outside the lab. Second, we are able to entirely exogenize starting prices across the marketplace, which is rare when using archival data on eBay or other platforms. Finally, we are able to nullify the impact of overlapping auctions through our research design, thereby reducing any incidental information available from other auctions that are further along in duration (Bapna et al. 2009; Hyde et al. 2006). Our results show the significant effects that exist across starting prices in similar but differentiated markets.

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