ABSTRACT

Title of Document:	BUY NOW, THINK LATER: PRODUCT RETURNS AND FIRM PERFORMANCE
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This dissertation studies the short-term and long-term impacts of return policies and feedback text on firm performance. Archival data, text analytics, and econometric analysis are used to further develop signaling theory, transaction cost economics, and procedural justice theory in operations, logistics, and supply chain management.

The first essay is motivated by the ambiguity of prior research on the relationship between return policies and demand in the online setting. The return policy components that impact landed prices are identified and the relationships between terms of sale and demand are studied. After controlling for price, a lenient return policy is found to signal the unobservable quality of the seller's product and demonstrate their capability to properly handle sales, shipping, and returns. A lenient

return policy also helps mitigate customers' risk associated with a mismatch between the product and their expectations and is shown to be positively associated with landed price and demand.

The second essay demonstrates that the impact of a customer's satisfaction or dissatisfaction with a seller or their product extends to other customers when their satisfaction or dissatisfaction becomes public knowledge, impacting sellers' future demand. The impact of negative, trust revoking feedback is shown to differ from the impact of non-trust revoking, negative feedback, such as nonspecific complaints and complaints about price. In other words, the text associated with numerical feedback ratings determines the strength of the negative rating's impact. Moreover, it is shown that negative feedback can be altered and even counteracted with a satisfactory service recovery, while the variance of complaint types in sellers' feedback histories is negatively associated with demand.

Overall, this dissertation demonstrates the benefits of two signals of quality: a lenient return policy and positive feedback history. Methodological contributions include the use of two original datasets and the combination of text analytics and regression analysis to inform managerial decisions. Managerial implications suggest that firms should take the leniency of their return policies and the strength of their online reputations into consideration when pricing and estimating demand.

BUY NOW, THINK LATER: PRODUCT RETURNS AND FIRM PERFORMANCE

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctorate of Philosophy
2018

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Dedication

For my parents
in deep gratitude for all their love and support.

Acknowledgements

The completion of this dissertation marks the endpoint of a tremendous journey that I would not have completed without the support of many people.

Untold thanks to my family and friends who have been closest to me, for endless reasons, including their never-ending patience and support. I cannot describe the invaluable ways that Kate Ren has shaped my life and helped me throughout this process; I would not have completed this degree without her. Curt Grimm has also served as a tremendous role model, and I am so thankful to have had such a great leader during my time at Maryland.

I want to express my deepest gratitude to Robert Windle and Philip Evers for co-chairing my dissertation and providing me with invaluable direction during my pursuit of a doctoral degree. I am deeply grateful for the knowledge they shared with me throughout my entire PhD program and dissertation – I would not have completed this journey without their guidance and support. I am extremely grateful for the many hours they spent helping to shape and craft my dissertation.

I am deeply grateful for the knowledge and wisdom Martin Dresner shared with me in his doctoral seminar and office hours. I deeply appreciate the time, effort and advice he offered. He has been a great mentor throughout my PhD program, and I am proud to have him on my doctoral committee. I would also like to thank Cinzia Cirillo and Anand Gopal for kindly agreeing to serve on my dissertation committee and generously sharing their thoughts and expertise.

The entire Logistics, Business and Public Policy department at the Robert H. Smith School of Business has been extremely supportive and generous over the previous five years. I was lucky enough to work with and learn from several excellent colleagues, including Tom Corsi, Charles Olson, Stephanie Eckerd, Jahangir Boroumand, Bennet Zelner, Holly Zhang, Brian Nelson, Mary Ann Wagner, and Dianne Fox. I sincerely appreciate all the wisdom you shared with me.

I also appreciate my fellow doctoral students that made my experience at Maryland an extremely enjoyable one. Thank you to Anupam Kumar, Kevin Sweeney, Omar Elwakil, Heidi Celebi, Isaac Elking, John Patrick Paraskevas, Camil Martinez, Kate Ren, Xiaodan Pan, Rohan D'Lima, Laharish Guntuka, Hao Su, and Kevin Park.

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Chapter 1: Signals in Competitive Markets

Most markets within online marketplaces, such as Amazon, eBay, and Taobao, are highly competitive. Of the four assumptions of competitive markets (see below), these marketplaces consistently and strongly satisfy three.

A1.Numerous buyers and sellers

A2.Free entry and exit

A3.A homogenous product

A4.Perfect information

On eBay there are currently over 168 million active buyers and over 25 million active sellers (Forbes, 2017). Similarly, over a seven-month period greater than 972 eBay sellers were observed selling Bose QC25 headphones with identical specifications. Furthermore, hundreds of sellers of the Bose QC25 headphones can be found on the Amazon Marketplace offering the identical product, years after its release. Thus, assumption (A1) is clearly satisfied for most products: numerous buyers and sellers exist in online marketplaces. With greater than one billion live listings on eBay and more than 680,000 new sellers on the Amazon Marketplace each year (Marketplace Pulse, 2018), along with virtually no startup costs, there is clearly free entry and exit (A2). While virtually any product can be sold in an online marketplace, most listings are for standardized products, especially in the consumer electronics category (Forbes, 2017). In addition, the number of listings for new products dominates the listings of

used and refurbished items. Over three quarters (81%) of the listings on eBay are for new products (Stevens, 2016) and the same can be said for Eachnet.com (Cai et al., 2013) and PriceMinister.com (Jolivet et al., 2016). This includes the auction listings on eBay ("the World's largest auction platform"), which are often for older, used, or collectible items. Thus, for most online marketplaces, assumption (A3) is confirmed.

The fourth assumption, however, is less certain. When buying online, there is both spatial and temporal distance between the buyer, seller, and product, complicating decisions regarding product fit and increasing outcome uncertainty for both the buyer and seller.

Many marketplaces, have taken measures to combat the complications associated with imperfect information, including the establishment of reputation mechanisms and the introduction of signals and designations that reflect seller and product quality. For example, eBay prominently displays feedback scores, star levels, and experiential badges on each listing. Amazon uses a five-star rating system and displays the percentage of positive ratings over the previous 12 months to help its customers distinguish between reputable and non-reputable sellers. Taobao.com uses a similar system of ratings, comments, and complaints to help buyers assess seller backgrounds.

The two essays of this dissertation examine the influence of two signals of quality on operational performance: lenient return policies and positive feedback profiles. Essay 1 identifies the tradeoffs between return policy leniency and landed price, from

both the buyer and seller perspectives. The values of different return policy components are estimated and their relative influence on supply and demand are quantified. The second essay examines the impact of buyer feedback on demand. Trust-revoking and non-trust-revoking complaints are distinguished to separate the influence of feedback text from oft-studied numerical ratings. The influence of complaint type dispersion and the volume of service recoveries are also investigated.

Positioned at the marketing–operations interface, essay 1 tests the assumption that a lenient return policy is a valid signal of quality in an online marketplace. Several contributions are made to the emerging literature on product returns. First, the value that online sellers place on lenient return policies is estimated through an evaluation of the landed prices they charge. Second, the impact of four return policy components (i.e. return window, non-refundable shipping charges, return shipping fees, restocking fees) are distinguished by their impact on supply. Third, the impact of three terms of sale (i.e. return policy, shipping charge, price) on demand are estimated with buyers' reactions to return policies, shipping charges, and price combinations on the time to sale for each listing.

A unique sample, including all fixed price listings of six identical consumer products sold on eBay over the course of nine months, is utilized to test the hypotheses of essay 1. The data includes complete information on each transaction, including measures of product description, product presentation, listing timing, and seller reputation. The terms of sale, including the return policy, price, and shipping service

and cost, are also recorded for each listing. The data includes over 24,000 transactions by over 6,000 retailers.

Return policy leniency is found to be positively associated with landed price (supply), which is a function of the product price and shipping charges and is determined by the seller. It is found to be significantly influenced by the length of the return window, but less so by restocking fees or free return shipping. Thus, sellers do not build the cost of free return shipping or restocking fees into the landed price for their listings.

On the other hand, non-refundable shipping charges, which are a form of *implicit* restocking fee were found to significantly impact supply. Free shipping is shown to be positively associated with landed price, suggesting that buyers are willing to pay a higher landed price to avoid the possibility of losing non-refundable shipping charges.

Meanwhile, (explicit) restocking fees were found to be the primary return policy parameter impacting time to sale (demand), which is driven by customers' reactions to the sellers' terms of sale. The length of the return window and free return shipping were not found to impact time to sale.

These results offer evidence on the value of lenient return policies as signals of quality in online marketplaces and extend the product return literature by decomposing

the value of different return policy components. A path for future research is also presented and many research opportunities are described.

The second essay examines if and how customer satisfaction and dissatisfaction extend to other customers when their satisfaction or dissatisfaction becomes public knowledge. The impact of trust-revoking complaints is compared to the impact of non-trust-revoking complaints to identify the degree of influence of feedback comments compared to numerical seller ratings. The impact of successful service recoveries documented in feedback text are examined, and complaints are distinguished by their focus. The following research questions are examined:

1. Does the impact of negative feedback on landed price and time to sale vary by complaint type?
2. Do successful service recoveries mitigate the negative impact of buyer complaints?
3. Does the variety of complaint types explain the non-linear impact of negative feedback?

To answer these questions, over 1.5 million feedback posts from eBay are collected, and a combination of content analysis and text classification are used to produce numerical ratings reflecting seller skill and reputation within the eBay marketplace. From these, seller-specific measures related to positive threads, neutral threads, negative threads, service recoveries, complaint free threads, trust-revoking complaints,

non-trust revoking complaints, and complaint type dispersion are calculated and used in a two-stage least squares regression model to test six hypotheses.

The results reveal that service recoveries impact both landed price and time to sale, while trust-revoking complaints and complaint type dispersion have a significant impact on landed price (supply) but do not significantly impact time to sale (demand). This demonstrates that both customers and sellers pay attention to feedback text, with service recoveries positively impacting landed price and reducing the time to sale. However, sellers focus more on the type of complaints in their feedback history and adjust their landed price accordingly, while the time to sale remains unchanged.

Finally, chapter 4 concludes with a discussion of the implications of this dissertation and highlights its contributions from both a research and strategic perspective. The final chapter also links the implications of the two essays and outlines an extensive research agenda for future research.

Chapter 2: Signaling Quality through Terms of Sale: The Impact of Return Policies in Online Retailing

ABSTRACT

In this chapter, the signaling value of a lenient return policy is discussed and empirically tested using data from a major online marketplace, eBay. The structure is as follows: Section 2.1 provides an overview of the product returns literature and states the research questions and contributions of this essay. Section 2.2 describes the data and empirical specification. The results are presented in Section 2.3, and Section 2.4 presents the research implications, managerial implications, and future research opportunities.

"eBay is a marketplace that allows users to offer, sell and buy just about anything in a variety of pricing formats and locations. The actual contract for sale is directly between the seller and buyer. eBay is not a traditional auctioneer." (eBay, 2017a)

INTRODUCTION

Lenient policies enabling customers to return defective, regrettable impulse, or otherwise unwanted goods are an expensive aspect of customer service in the modern business environment. Returns often represent three to four times the cost of similarly sized outbound shipments (Wang, 2009). In fact, firms in the United States spend an estimated $40 billion managing returns, each year (Enright, 2016). The U.S. electronics industry spent over $13 billion to repackage and resell returned merchandise, in 2007 alone (Lawton, 2008). However, despite such operational costs, retailers continue to allow returns as a customer service strategy; a choice, which according to Tom Enright, supply chain research director at Gartner, is a "ticking time bomb" in the age of multi-channel retailing (Enright, 2016).

Previous research has looked into many aspects of the returns management process, particularly at the retail level. For example Davis et al. (1998) demonstrated analytically that retailers are incentivized to offer lenient return policies when their products' consumption time is long, significant cross-selling opportunities exist, and salvage values of returned merchandise are large (Davis et al., 1998). A body of literature has also developed around inventory decisions and return contracts between the retailer and manufacturer (Cachon, 2003). Interest on the effective management of

backward flowing inventory for reuse and recycling purposes has also grown rapidly over the last decade (Fleischmann 2001, Guide 2000, Guide and Van Wassenhove, 2001). However, despite extensive work in these areas, there is a lack of empirical research documenting the relationships between return policies, price, and demand.

This study empirically measures the value of a lenient return policy and provides new insight into how return policies and other terms of sale impact demand. The following research question is studied: How do the components of retailers' return policies affect supply (landed price) and demand (speed of sale) in the online setting?

Several contributions are made to the emerging literature on product returns. First, the value that online sellers place on a lenient return policy is estimated through an evaluation of the prices they charge. Second, the impact of return policy components (i.e. return window, non-refundable shipping charges, return shipping fees, restocking fees) are distinguished by their impact on price. Third, the impact of three terms of sale (i.e. return policy, shipping charge, price) on demand are evaluated in the online setting.

To answer these questions, detailed information is collected on the transaction, product, and seller involved in fixed price (buy-it-now) listings of six identical consumer electronics products offered by different vendors – with various return policies – from eBay over the course of six months. The data includes complete information on each transaction, including detailed information about the product description and presentation and the sellers' feedback profiles. The terms of sale for

each listing, including the return policy, the price, and the shipping service and cost, are also recorded. The data includes over 20,000 transactions by over 6,000 vendors.

Return policy leniency is found to be positively associated with the landed price of completed sales. The length of the return window is positively associated with the landed price while restocking fees are negatively associated with time to sale. Thus, by signaling seller and product quality, a lenient return policy positively impacts demand while shipping charges and landed price are negatively associated with demand. Interestingly, an explicit restocking fee is shown to have a much greater impact on the landed price charged by sellers and on customer demand than an implicit restocking fee, in the form of a non-refundable shipping charge. Therefore, an opportunity exists for sellers to build in monetary protection against product returns through higher shipping charges.

LITERATURE REVIEW AND HYPOTHESES

In online marketplaces, significant information asymmetries exist, due to the spatial and temporal distance between the buyers and sellers. Customers do not have the opportunity to "touch and feel" a product prior to purchase, and only learn its true value post-sale. In online marketplaces, such as eBay and Amazon Marketplace, with many small to medium sized sellers, there are often very few repeat transactions. In fact, Resnick and Zeckhauser (2002) found that only 11% of eBay buyer-seller pairs conducted more than one transaction over the course of five-months. In many cases,

there are also hundreds or thousands of sellers offering the same product. For example, I observe over 4,500 sellers of GoPro Hero4 cameras on eBay over nine months. As a result, buyers are typically unaware of an individual seller's ability to manage the sales and returns processes, the quality of the seller's product, and their own valuation of the product, due to the lack of physical inspection prior to purchase. In this setting, customers must assess the value of the product and the capability of the seller from the seller's characteristics, the product description, and the terms of sale, defined by Anderson (1947) as:

> *"Those specific conditions as to the basis of pricing, billing, and delivery by the seller, and those specific conditions as to the payment by the buyer, which constitute an integral part of the sales transaction."*

Terms of sale vary by industry and seller, but commonly include price, quantity, delivery conditions (e.g. item location, processing, packing, and shipping charges), payment conditions (e.g. taxes and interest charges), liability conditions (e.g. performance warranties), and return conditions (e.g. return shipping charges, scrap value) (Anderson, 1947). Many terms of sale have been investigated in the operations management, information systems, and marketing literature, including price (Gerstner, 1985; Ketzenberg and Zuidwijk, 2009; Abbey et al. 2015), warranties (Spence, 1977; Wiener, 1985, Huang et al. 2007) and money-back-guarantees (Ketzenberg and Zuidwijk, 2009; Anderson et al., 2009; Rao et al., 2017; Shang et al., 2017b), among many others. The present study complements this stream of research by considering the

impact of three terms of sale: price, shipping charge, and return policy, in the online setting.

Previous research suggests that return policies are a managerial lever that can be used to signal quality and influence demand. Theoretically, a lenient return policy acts as an effective signal of quality by exploiting the fact that lower-capability sellers experience a higher likelihood of product returns and associated transaction costs. A lenient return policy stimulates demand by reducing "product quality uncertainty" (Moorthy & Srinivasan, 1995), "consumer valuation uncertainty" (Su, 2009), and "product fit uncertainty" (Hong and Pavlou, 2014). Theory suggests that a lenient return policy signals the quality of the product and the seller, thereby lowering customers' transaction costs, and encouraging them to enter the market (Li et al., 2009).

Empirical research, however, is only just beginning to test these theories. Anderson et al. (2009) found a mail-order apparel company to earn a 20-30% price premium when the option to return merchandise was offered. Shang et al. (2017b) found that eBay sellers offering a money-back guarantee earn a 5.2% price premium over sellers that do not, and this price premium is amplified by a positive online reputation. In both studies, a money-back guarantee was defined as any policy where returns are accepted under the default conditions and no distinction is made between the length of the return window, the existence of restocking fees, or the cost of return shipping.

Similarly, Rao et al. (2017) found return time leniency to be an effective signal of unobservable product quality in the online setting. Using live online auctions, they demonstrate that the higher signaling costs of a longer return window do increase consumers' willingness-to-pay, by reducing information asymmetry. However, they also find this effect to be concave curvilinear. Thus, the benefits of return time leniency are most profound on the lower extreme and subject to diminishing marginal returns approaching the upper extreme.

Overall, there is an acknowledged lack of empirical research on the signaling value of return policies, especially in the supply chain management discipline (Mollenkopf and Closs, 2005; Mollenkopf et al., 2007; Mollenkopf et al., 2011; Grifis et al. 2012). Furthermore, calls have been made to examine return policy components other than return time leniency in the online setting (Shang et al., 2017b; Rao et al., 2017).

The current study fills this research gap by examining three terms of sale: price, shipping charge, and return policy, with respect to their impact on demand in an online market. Clear tradeoffs exist among these three terms of sale: sellers can design many equivalent listings for an identical product by varying the price charged, the leniency of the return conditions, and the cost of shipping. The goal of this study is to examine how online retailers view these tradeoffs and to compare those views to the actual purchasing behavior of buyers, with the primary variable of interest being the return policy. An attempt is also made to place a value on the different return policy

components. To do so, we draw from three theories: signaling theory, transaction cost economics, and institutional theory. Each is discussed in the following subsections.

Return Policies and Signaling

In competitive markets characterized by significant information asymmetry, it becomes imperative for sellers to signal their quality to potential buyers. To qualify as a signal, a characteristic must be observable, subject to manipulation by the seller, and costly to acquire (Spence, 1973). To be effective, a signal must be inexpensive enough for the high-capability sellers to acquire it, and sufficiently costly to deter low-capability sellers from doing so (Spence, 1973). The classic example is a college degree. High capability individuals find it less costly than low capability individuals to obtain a college degree and therefore, elect to do so to distinguish themselves in the job market. Other signals include advertising (Kihlstrom and Riordan, 1984; Milgrom and Roberts, 1986; Kirmani, 1990), branding (Rao et al., 1999), nonprofit status (Chesteen et al., 2005), levels of inventory (Lai, 2006), certifications (Gopal and Gao, 2009), and warranties (Boulding and Kirmani, 1993; Soberman 2003; Chu and Chintagunta, 2011).

In this paper, we extend the signaling literature by studying how a return policy acts as a signal in the online context and empirically demonstrating the value of four different return policy components from both the buyer and seller perspectives. Theoretically, after controlling for price, a lenient return policy signals the unobservable quality of the seller's product and demonstrates their capability to

properly handle sales and returns management (Moorthy and Srinivasan, 1995). The return policy signal suggests lower risk and higher security of the transaction and should be offered by more reputable sellers. Through this signal, high quality sellers should differentiate themselves from less reputable sellers and earn a price premium that offsets the cost of providing the signal (Spence, 1973).

On eBay, sellers have the freedom to customize many aspects of their return policies (see Ap. A). They can select the length of the return window, determine the party that is responsible for paying the return shipping (i.e. buyer or seller), charge restocking fees, and apply conditions on the items eligible for returns. Sellers can also impose nonrefundable shipping charges, which are a less obvious, "implicit," restocking fees. Long return windows, free return shipping, free (or low) shipping charges, and the lack of restocking fees and return eligibility restrictions are considered lenient. Short return windows, large forward and reverse shipping charges, restocking fees, and return exclusions are considered strict.

A lenient return policy is costly, because it opens the door for additional return merchandise, which must be processed and perhaps refurbished, aesthetically restored, relisted, or even scrapped. A lenient return policy also increases the likelihood of return abuse (Griffis et al., 2012) aka "retail borrowing" (Piron and Young, 2000) aka "wardrobing" (Shang et al., 2017a). Intuitively, a longer return window should be associated with a higher volume of returned merchandise. Similarly, the absence of

return shipping charges and restocking fees decreases customers' cost of returns and encourages them to send more products back.

Since the marginal cost (i.e. the quantity and handling costs of returned merchandise) is lower for high-capability sellers than for low-capability sellers, a lenient return policy qualifies as an effective signal of quality and capability that distinguishes a seller from its competitors (Moorthy and Srinivasan, 1995). Sellers should be more inclined to offer a lenient return policy if they are confident in the quality of their product and their ability to repackage and recoup value from returned merchandise. If these high-capability sellers expect to earn a price premium from their return policy signal, then they will charge a higher price for an identical item than a seller with a less lenient policy. Therefore, based on signaling theory, we propose the following hypothesis:

Hypothesis 1: *Lenient return policies are positively associated with landed price.*

In practice, restocking fees are rare and often viewed as unfair by customers, especially for experiential goods (Bower and Maxham, 2012). For example, customers may view restocking fees as unreasonable for innovative products with short product descriptions. However, by default, customers returning merchandise on eBay pay another, less obvious, restocking fee: the nonrefundable shipping charge to acquire the good(s). This "implicit" restocking fee should also be negatively associated with price; however, because it is paid at the time of purchase (i.e. when customers expect to retain

the product), instead of the time of return (i.e. when customers are dissatisfied with the product), sellers may expect it to have less of an impact than explicit restocking fees. Furthermore, since shipping charges are nonrefundable by default on eBay, while the seller must specify restocking fees, these *implicit* restocking fees may have less impact on the prices charged. In other words, even if the monetary value of the fees is equal, sellers believe they can mask these *implicit* restocking fees, because they are the marketplace standard; however, they must reduce their price dramatically if they charge an *explicit* restocking fee, which is rarely used in the marketplace.

Since free shipping eliminates the sunk costs that would be lost due to product returns, there should be a positive association between free shipping and the landed price buyers are willing to pay. Based on these arguments, the following is proposed:

Hypothesis 2: *Free shipping is positively associated with landed price.*

Return Policies and Transaction Costs

Due to the information asymmetry inherent in online markets, customers face a great deal of uncertainty when making purchases online, and this uncertainty increases the transaction costs that buyers face when selecting a supplier (Williamson, 1975, 1979). As a result, customers may be reluctant to purchase products from a seller with a strict return policy, due to the risk of product misfit and the significant transaction costs involved in the process. A lenient return policy meanwhile, helps to mitigate

customers' risk by providing them the ability to send back the products that do not fit their expectations/unique taste.

Theoretically, a longer return window provides customers with additional insurance against product and outcome uncertainty and encourages customers to "take more chances" (Moorthy and Srinivasan, 1995; Hong and Pavlou, 2014). The absence of return shipping charges and restocking fees reduces customers' transaction costs by reducing customers' risk of product "misfit," the penalty for ordering an unsatisfactory product. Moreover, previous research has shown that having to pay return shipping significantly decreases customer loyalty (Griffis et al., 2012). Simply experiencing a seller's returns process, lowers the uncertainty inherent in future transactions with that seller. Griffis et al. (2012) empirically demonstrated that returns-experienced customers purchase more frequently, more items per order and higher value items.

Thus, consistent with signaling theory and transaction cost economics, a lenient return policy should increase demand by signaling the quality of both the seller and the product and reducing customers' transaction costs. Elevated demand should be reflected in lower time to sale. We thus propose:

Hypothesis 3: L*enient return policies are negatively associated with time to sale.*

DATA AND MODEL

The following subsections provide an overview of the data collection, data cleaning, and variable creation procedures. For a complete description of these processes, see Appendix B.

Data Collection and Cleaning

Using a structured web-crawling procedure, data were gathered on all transactions involving six identical consumer electronic products sold on eBay from February 14, 2015 to November 19, 2015. More specifically, detailed information was collected on the transaction, product, and seller involved in fixed price listings of new GoPro Hero4 Black (1), Silver (2), and Session (3) edition cameras, Microsoft Xbox One entertainment systems with (4) and without (5) Kinect, and Bose QC25 (white, black, and custom editions) headphones (6). The specifications of the Hero4 cameras vary greatly, and as a result they are considered three distinct models. However, the specifications are identical across the white, black, and custom versions of the QC25 headphones, and they are therefore considered a single product. Differences in demand for the color of the interior and exterior pads is controlled for.

The search was restricted to new products and fixed-price (buy-it-now) listings offered by US sellers. The fixed price format differs from eBay's traditional auction environment; however, it corresponds with the site's recent bid to attract new, younger consumers by shifting away from the bid and wait approach and allowing customers to

purchase items instantaneously. Currently 80% of the items on eBay are new and 86% are sold at a fixed price (Stevens, 2016).

The web-crawling script began by searching "xbox one," "gopro hero 4," and "bose qc25" in the eBay advanced search tool[1]. This generated a complete set of listing URLs, which were then cycled through to collect detailed information about the product description, presentation, price, shipping service, and return policy. Seller characteristics (tenure, feedback ratings, text comments) were then collected through the seller feedback URLs on the listing pages.

The web-crawling script was run in the middle of each month from May to November in 2015. Based on eBay's policy of storing records of sales for 90 days and unsold listings for 30 days, the entire set of transactions for the six base products were collected. After eliminating repeat transactions, the raw (uncleaned) listings data includes 24,824 transactions by 7,006 vendors. GoPro cameras (Black, Silver, and Session editions) account for approximately 43% of the sample, Xbox One entertainment systems account for approximately 47%, and QC25 headphones account for the remaining 10%.

[1] http://www.ebay.com/sch/ebayadvsearch

To determine the product(s) involved in each transaction, the title and description of each of the 24,824 listings were manually read and categorized based on content. From this process, 13,187 (53.12%) of the transactions were found to involve the standard, base product and package. Meanwhile, the standard product was bundled with other products or accessories in 1,965 transactions (7.92%) and special edition models (with or without accessories) accounted for the remaining 8,621 transactions (34.73%).

Since the special edition models could easily be identified using manufacturer provided identifiers (MPN) and barcode symbols (UPC-A), they were retained in the sample. Differences across these special edition models are accounted for with product- and item-specific controls. The bundles, which often included carrying cases for the Bose headphones, games for the Xbox entertainment system, and mounts for the GoPro camera, varied greatly in their contents, and were therefore removed. For more information on these variables see Ap. B.

From the remaining listings, the contents of 1,051 listings (4.23%) were deemed unclear and tagged for removal. Listings that did not include the primary product, such as listings that only included Xbox games or GoPro accessories, were also removed. Although, the web crawling script was designed to search for new, unopened products, some discrepancies remained. After carefully examining the listing titles, 80 listings that were either used, open box, or without the box were tagged for removal. An additional 151 listings that did not include the standard accessories, such as the wireless controller and power supply for the Xbox One, were removed. Transactions with either

origin or destination outside of the U.S. were also removed to avoid differences in the perceptions of return policies across cultures. Finally, all observations with missing variables were removed.

eBay sellers can elect to hide certain elements of their seller profile after a given amount of time. As a result, some sellers had missing information and were omitted from the analysis. A small proportion of sellers did not receive any negative or neutral feedback ratings the twelve months prior to the creation of their listing. Thus, if the natural logarithm of the total number of neutral and negative feedback ratings is taken, as is commonly done to control for the nonlinear impact of seller reputation, these values could not be calculated and therefore, these sellers would be dropped from the analysis. Therefore, percentage measures of seller reputation are used in the primary analysis, and alternative feedback measures using logged values are used in a robustness check.

Unsold listings were also removed to eliminate extreme pricing decisions and censored time to sale values, reducing the sample by 4,004 observations.

Finally, to avoid extreme outliers, an equal percentage of the top and bottom landed prices and time to sale values were trimmed. These listings typically included either a very large bundle of products or were limited to accessories. A low, 5% value was selected to avoid over fitting the data; however, alternative values (1%, 3%, 10%) were

created to ensure robust results. More information on the trimming process is provided in Appendix B.

After the completion of the data cleaning and variable creation process, 8,351 observations remained for estimation.

The next three subsections describe the measures used in the regression analysis. The variables are described in table 1 and the descriptive statistics are offered in table 2.

Dependent Variables

This study focuses on the impact of two terms of sale on demand: the return policy and the landed price, both of which are determined by the seller. In practice, sellers adjust their prices much more frequently than their return policy. In fact, less than 5% of the retailers in our sample changed their return policy over the course of six months. Therefore, we consider the return policy decision to be exogenous and focus on the across seller variation in return policies and its impact on demand.

Econometrically, a two-equation supply and demand model is estimated. Supply is represented by the landed price charged for the listing (*Landed Price*) and demand is represented by the speed of sale (*Time to Sale*). A two-stage least squares model is used to account for the impact of the return policy on demand. First, the landed price (supply) is estimated and each of the return policy components are included in the estimation. Then, the fitted value of the landed price and the return policy components are used to

estimate the time to sale (demand). Transaction-, seller-, and product-related controls are included in both equations.

Landed Price

In the first equation, the total landed price (*Landed Price*) of the fixed-price listings are estimated. These prices, which are determined by the seller, include both the price to purchase the product(s) as well as the shipping charge, if any. Only fixed-price listings are included and all "best offer accepted" listings are dropped prior to analysis, removing the possibility of a seller accepting a price other than her list price, and avoiding the traditional auction format used on eBay. Landed Price is a function of the product(s) in the listing, the seller's return policy, their product presentation, and their online reputation.

As shown in table 1, the average landed price in the sample is $357.54. The average landed price (standard deviation) of the Bose QC25 headphones (all colors), GoPro Hero4 (all versions), and Microsoft Xbox One (with and without Kinect) were $254.08 (12.14), $377.86 (41.36), and $358.99 (42.93), respectively.

Time to Sale

The second dependent variable, *Time to Sale*, is determined by the market and reflects the demand for an individual listing. Demand is a function of whether the product(s) sold, the speed of sale, and the quantity purchased. However, in this setting, which includes many infrequent, low-volume sellers, most sales involve only a single

unit. In fact, less than 1% of the completed transactions in the sample involve more than one unit. To avoid biasing the results with listings that were removed prematurely or that were assigned new listing IDs due to minor changes in terms, such as a slight alteration of the listing price, only listings that resulted in a sale are included in the analysis. Therefore, the Time to Sale, equal to the time (i.e. days, minutes, seconds) between the initial product offering and the time the product(s) sold, is used to measure demand. To the authors' best knowledge, this dependent variable, which captures the "time on market" has not been looked at in the context of online retailing. It is however, a popular variable of interest in the real estate (Knight, 2002) and financial economics literature (Israel and Moskowitz, 2012).

Figure 1 displays a histogram of the *Hours to Sale*. The average time it takes for a listing to close is 47.48 hours (1.96 days). The fastest time to sale is approximately half an hour (.55 hours) and the longest is over twenty-two days (542 hours). On average, the Bose QC25 headphones sold the quickest, with an average *Time to Sale* of 32.01 hours, followed by the Xbox entertainment system with an average of 42.61 hours. The GoPro models took the longest to sell, averaging 55.23 hours from listing creation to listing close.

Table 1: Variable Descriptions

Variable	Description
Landed Price	Per unit price (including shipping) offered by the seller.
Time to Sale	The time (days, hours, minutes) between the creation of the listing and sale of the product.
Return Policy	
Returns Allowed	Whether product returns are permitted (1) or not (0).
Shorter Window	Whether a return window less than the default (1-13 days) is offered (1) or not (0).
Default Window	Whether the default (14-day) return window is offered (1) or not (0).
Extended Window	Whether a return window greater than the default (14+ days) is offered (1) or not (0).
Free Shipping	Whether shipping is free of charge (1) or not (0).
Free Return Shipping	Whether the seller (1) or buyer (0-default) is responsible for return shipping charges.
Restocking Fee	Whether any restocking fee is charged on returned merchandise (1) or not (0).
Restock 10%	Whether a 10% restocking fee is charged on returned merchandise (1) or not (0).
Restock 15%	Whether a 15% restocking fee is charged on returned merchandise (1) or not (0).
Restock 20%	Whether a 20% restocking fee is charged on returned merchandise (1) or not (0).
Restock Other	Whether a non-standard restocking fee is listed in the seller's detailed return policy (1) or not (0).
Transaction Characteristics	
Description Length	The thousands of characters, including spaces, in the item description section of the listing page.
Images	The number of product images displayed on the listing page.
Percent Ship Charge	The percentage of the landed price attributed to shipping and handling.
Previously Sold	Whether the quantity of previously sold, identical units is displayed on the listing page (1) or not (0).
Seller Characteristics	
Seller Tenure	The number of years between the sale date and the creation of the seller profile.
Percent Positive	The percentage of ratings the seller has received in the last year that are positive.
Percent Negative	The percentage of ratings the seller has received in the last year that are negative.
Positive	The hundreds of positive feedback ratings the seller has received in the last year.
Neutral-Negative	The number of neutral and negative feedback ratings the seller has received in the last year.
Product Characteristics	
One TB HDD	Whether an upgraded, 1 TB, hard drive is included in a special edition Xbox listing (1) or not (0).
Kinect	Whether the Kinect sensor is included in an Xbox listing (1) or not (0).
Weeks from Launch	The number of weeks between the sale date and the product launch.
Preorder	Whether the sale date occurred prior to the release of the product (1) or not (0).
Shipping Services	
Economy	Whether economy (2-9 day) shipping is included (1) or not (0).
Standard	Whether standard (1-5 day) shipping is included (1) or not (0).
Expedited	Whether expedited (1-3 day) shipping is included (1) or not (0).
Overnight	Whether overnight (1 day) shipping is included (1) or not (0).

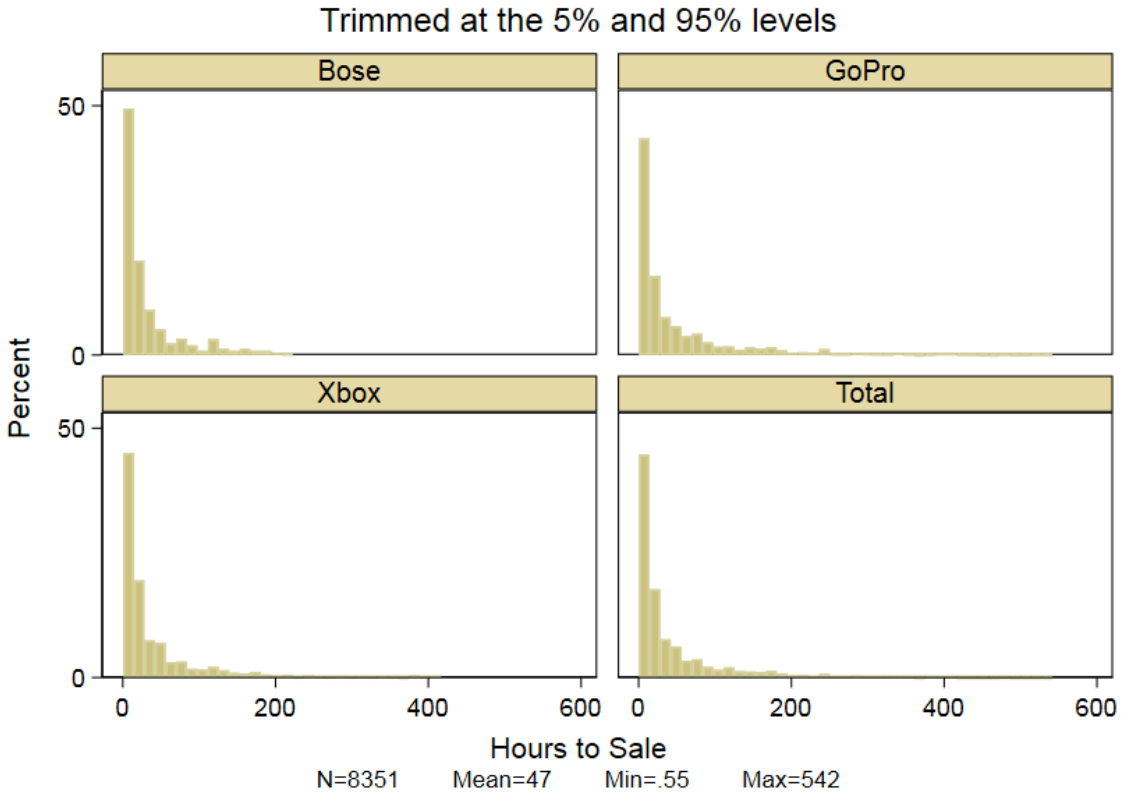
Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Landed Price	357.54	53.45	223.04	495.00
Time to Sale (hours)	47.47	75.81	0.55	541.50
Listing Characteristics				
Description Length (000 chars.)	7.79	1.55	4.70	14.98
Images	2.90	2.26	1.00	12.00
Percent Ship Charge (%)	1.00	2.00	0.00	22.00
Previously Sold	0.31	0.46	0.00	1.00
Product Characteristics				
One TB HDD	0.10	0.30	0.00	1.00
Kinect	0.06	0.24	0.00	1.00
Weeks from Launch	36.79	19.93	0.00	103.10
Preorder	0.01	0.10	0.00	1.00
Seller Characteristics				
Seller Tenure (years)	6.94	4.91	0.00	18.68
Percent Positive	0.97	0.12	0.00	1.00
Percent Negative	0.01	0.05	0.00	1.00
Positive (hundreds)	14.28	80.73	0.00	864.67
Negative-Neutral	21.72	153.90	0.00	1645.00
Return Policy				
Returns Allowed	0.47	0.50	0.00	1.00
Shorter Window	0.00	0.02	0.00	1.00
Default Window	0.43	0.50	0.00	1.00
Extended Window	0.04	0.19	0.00	1.00
Free Shipping	0.78	0.42	0.00	1.00
Free Return Shipping	0.01	0.11	0.00	1.00
Restocking Fee	0.09	0.29	0.00	1.00
Restock 10%	0.03	0.17	0.00	1.00
Restock 15%	0.02	0.13	0.00	1.00
Restock 20%	0.04	0.20	0.00	1.00
Restock Other	0.00	0.05	0.00	1.00
Shipping Services				
Economy	0.15	0.36	0.00	1.00
Standard	0.33	0.47	0.00	1.00
Expedited	0.51	0.50	0.00	1.00
Overnight	0.01	0.09	0.00	1.00

N=8,351

Note: Landed Price and Time to Sale were trimmed at the 5% level

Figure 1: Histogram and Descriptive Statistics of Time (Hours) to Sale



Independent Variables

Strong institutional norms exist on the eBay marketplace. These norms date back to the site's roots as an auction platform and are mixed with the current default return policy. On eBay the default return policy is to give money back for 14 days, with no restocking fees, and with the buyer paying for return shipping. The forward shipping fee is also nonrefundable, by default.

Despite these norms, eBay sellers are given the freedom to customize many components of their return policies, including the length of the return window, the presence of restocking fees, the party that is responsible for paying the return shipping (buyer or seller), and the shipping costs, which are nonrefundable (eBay, 2017b). Sellers can also provide buyers with the option to exchange or receive a replacement; however, this choice to up the buyer and a function of product availability. This parameter is therefore outside of the sellers' direct control and excluded from the analysis.

To change their terms of sale, eBay sellers must specify alternative components using the advanced listing tool (eBay, 2018d). As a result, most sellers elect to use the default return policy or disallow returns altogether, and alternative policies are typically used by very experienced sellers (Shang et al., 2017b). Additional return policy restrictions can also be specified on a seller's full, written return policy, which is listing-specific and available to buyers through a link on the listing page.

Because of this unique setting, substantial variation in the return policies for identical products can be observed. Nearly half (47.54%) of the transactions in our sample do not permit returns, approximately one third (33.56%) involve the default return policy, and the remaining 18.90% allow returns, but deviate from the default policy. In the following subsections, each of the return policy components are discussed in more detail.

Return Window

The default return window on eBay is 14 days. Therefore, a buyer must contact the seller within the two weeks following the sale to initiate a return. Under the advanced listing tool, sellers can extend their return window to 30 or 60 days or enter a custom value in the written return policy description. To test the impact of the return window on the Landed Price and the Time to Sale, three dummy variables are created: *Shorter Window*, *Default Window*, and *Extended Window*. *Extended Window* and *Shorter Window* represent deviations from the traditional institutional norm (of no returns) and the default (14-day) return window. By deviating from institutional norm and the default policy, these two policies represent potential signals in the marketplace. As hypothesized earlier, a deviation towards a more lenient return window is expected to signal the quality of both the seller and the product and result in a higher landed price (*Hypothesis 1*) and increased demand (*Hypothesis 2*). *Default Window* represents the default 14-day return window.

Return Shipping

On eBay, by default, the buyer pays the return shipping; however, sellers can elect to pay the return shipping, using the advanced listing tool (eBay, 2018d). To test the impact of this decision on the *Landed Price* and the *Time to Sale*, a dummy variable (*Free Return Shipping*) was created that takes a value of one if return shipping is free and is zero otherwise. As shown in table 2, free return shipping is very rare and was only offered in approximately 1% of the transactions. Thus, if free return shipping significantly impacts demand and allows sellers to earn price premiums, then significant opportunities exist to benefit from this option.

Restocking Fees

Like the length of the return window and the return shipping payment, restocking fees can be customized on eBay. The default return policy does not include restocking fees; and therefore, the full purchase price (minus the initial shipping charge) is refunded upon receipt of a return. However, using the advanced listing tool, eBay sellers can select from three standard restocking fee options of 10%, 15%, and 20% of the item price (eBay, 2018d). Sellers can also specify custom fees in their written return policies.

Both the return policies on the listing page and the sellers' custom return policies were checked for restocking fees. The restocking fees listed in custom return policies were identified through a combination of keyword (*restock, restocking, re-stocking*) and manual search.

A dummy variable (*Restocking Fee*) was created to account for the presence of any restocking fee, be it one of the standard options or an alternative percentage or dollar value specified in the written return policy. Disaggregate measures, representing the three standard options (*Restock 10%*, *Restock 15%*, and *Restock 20%*) and custom values (*Restock Other*) were also created and used in separate models. *Restock Other* captures all restocking fees other than the standard options. These could be large percentages of the product price, equal to the shipping charges, specific dollar values, or completely unspecified values. The common element amongst *Restock Other* is that these fees require additional effort on the buyer to locate and comprehend.

As shown in table 2, approximately 9% of the observations include restocking fees. The 20% restocking fee was the most common and restocking fees as large as 50% were observed. *Restock Other* captures restocking fees other than the standard options (10%, 15%, 20%) that were added to the seller's detailed return policies.

Free Shipping

In buy-it-now (BIN) auctions, eBay sellers are given the freedom to select their shipping service and cost. Shipping services include: economy (2-9 business days), standard (1-5 business days), expedited (1-3 business days), and one day; and typically range from $2 to $30. A no shipping (local pickup only) option is also offered; however, it is not observed in the sample. Sellers have three cost options: free shipping, flat-fee shipping, and calculated shipping. A flat rate freight shipping charge is also available for items over $150, but was only used in four cases, which were therefore removed.

The average shipping charge in this setting is $3.20 and the highest observed is $54.30. Economy, standard, expedited, and overnight shipping services were offered 15%, 33%, 51%, and 1% of the time, respectively. Shipping was free of charge 78% of the time, and a dummy variable (*Free Shipping*) is used to account for this option.

Control Variables

The literature suggests that in the online setting supply (*Landed Price*) and demand (T*ime to Sale*) are influenced by both the product presentation and seller characteristics (Lucking-Reiley et al. 2007; Shang et al., 2017b; Subramanian and Subramanyam, 2012). Support has also been found for additional factors, including: product condition, warranties, and accessories, impacting ending auction prices (Zhou et al., 2009). Therefore, following prior hedonic pricing research on online markets, three sets of control variables are included in the analysis: transaction-related controls, seller-related controls, and product-related controls. Table 1 categorizes and describes each variable and the following subsections outline the variables included in the empirical model.

Transaction-related Controls

A set of transaction-related control variables that have been shown to impact prices in previous research (Rao et al., 2017; Shang et al., 2017; Subramanian and Subramanyam, 2012) is included in the empirical model. These variables include: the length of the item description on the listing page (*Description Length*), the number of product images displayed (*Images*), the percentage of the landed price attributed to shipping and handling (*Percent Ship Charge)*, and whether the quantity of previously

sold, identical units are displayed (*Previously Sold*). The average product description is 7,792 characters, approximately three (2.90) images are displayed per listing, and the previously sold information is displayed 31% of the time.

Four shipping services are present in the data: *Economy*, *Standard*, *Expedited*, and *Overnight*, which represent 1-7-day, 1-5-day, 1-3-day, and 1-day services, respectively. To account for these different services, *Percent Ship Charge*, which represents the percentage of the landed price attributed to shipping and handling, is included in all models. As shown in table 2, shipping and handling account for an average of 1% of the landed price.

Seller-related Controls

After every transaction, the eBay buyer and seller have an opportunity to leave feedback on the other party. (See Ap. A for a detailed description of the process). These feedback ratings have consistently been shown to impact the prices charged by online sellers and buyers' willingness-to-pay (Cabral and Hortacsu, 2010; Resnick and Zeckhauser, 2002; Houser and Wooders, 2006, Subramanian and Subramanyam, 2012; Shang et al., 2017b). Therefore, several literature-based seller-related controls are included in the empirical model.

Standard practice is to combine neutral and negative ratings into a single measure and then take the natural log of this value to account for the nonlinear impact on price and demand (Cabral and Hortacsu, 2010; Resnick and Zeckhauser, 2002; Subramanian and Subramanyam, 2012; Shang et al., 2017b). However, our sample includes several

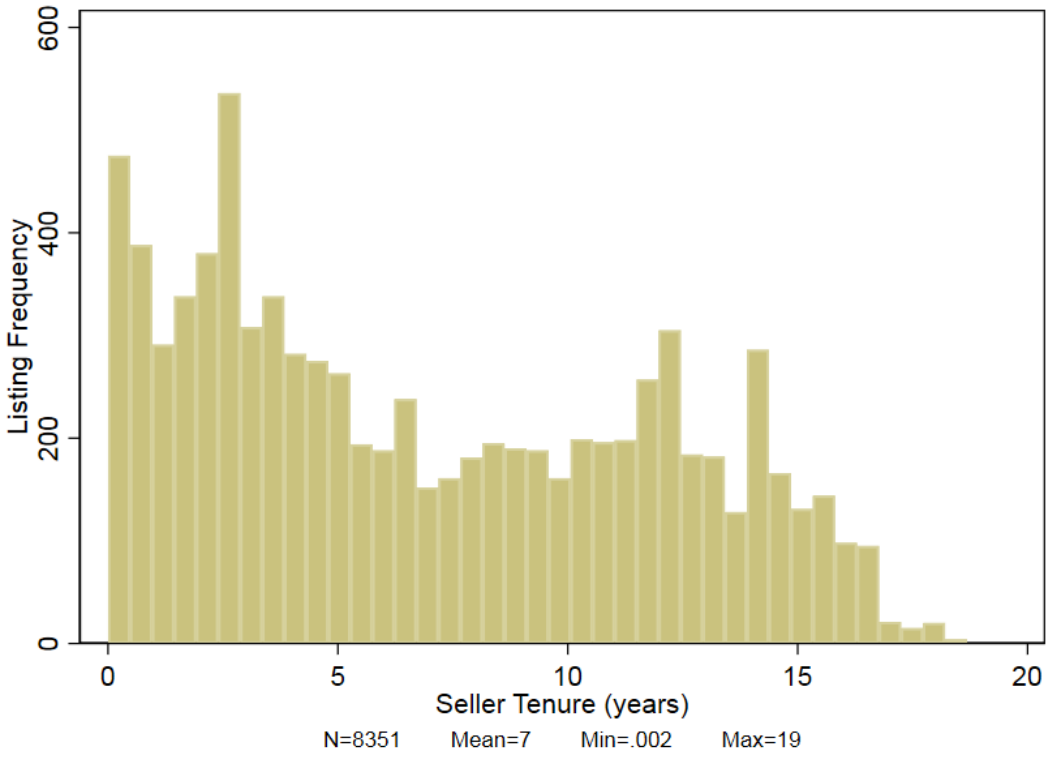
infrequent sellers that have zero neutral and negative ratings over the previous twelve months. Taking the natural log of these sellers' ratings, would exclude them from the analysis, and replacing null values with arbitrarily low values (e.g. 0.01) is subjective and potentially misleading. Instead, the percentage of the seller's total ratings that are positive (*Percent Positive)* and negative (*Percent Negative*) one year prior to the sale are used. The results using the unadjusted, logarithmic values of positive (*Log Positive)* and neutral or negative (*Log Neutral-Negative)* ratings in the previous year are also used in a robustness check. In this alternative specification, sellers without any positive, neutral, or negative ratings over the previous year are excluded from the estimation.

Conflicting evidence exists on whether buyers perceive neutral ratings the same as negative ratings. Recent evidence reveals that auction outcomes are sensitive to neutral ratings as well, and ratings of this type have been shown to have differential effects depending on the seller's overall proportion of positive and negative ratings (Rabby and Shahriar, 2016). As Rabby and Shahriar (2016) show, sellers with a high proportion of positive ratings are negatively affected by neutral ratings, whereas neutral ratings increase the demand for products sold by sellers with a high proportion of negative ratings. We consider this potential nonlinearity in our discussion.

Finally, *Seller Tenure* is included to account for sellers' pricing and listing expertise gained through market experience and for the uncertainty reduction from "older" sellers' more extensive feedback profiles. As shown in figure 2, the sellers in the sample are moderately experienced, with an average tenure of 2,555 days or 7.00 years across all listings. The longest tenured seller in the sample created their profile

approximately 19 years (6,820 hours) prior to an observed sale, and the lowest *Seller Tenure* is less than a day (18.27 hours).

Figure 2: Histogram and Descriptive Statistics of Seller Tenure



Product-Related Controls

During the product identification stage of data cleaning, several special edition models were discovered. Examples of special editions include: Xbox models with upgraded hard drives, Xbox models paired with new release games, and uniquely colored Bose headphones. Therefore, twenty product-specific fixed effects are included in the analysis to account for unobserved variations in supply and demand across products. The least expensive item (on average), the White Bose Qc25 headphones

(*Bose White)*, was selected as the base product and therefore, all product-specific dummies are expected to be positive and significant in the supply (*Landed Price)* equations. The product dummies in the *Time to Sale* equations, represent deviations in demand away from the *Bose White* headphones.

One manufacturer-specified special edition of the Bose QC25 headphones is observed: The Triple Black edition. The specifications for this product were identical to the black and white models, and the only difference was the color of the interior and exterior pads. To account for differences in demand for this "limited edition" color, a *Bose Custom* dummy was created. Other less common editions, such as the tan, beige, brown, blue, and gold editions were also grouped into the *Bose Custom* category.

Bose Black and *Bose Custom* are included in all models to differentiate between the color of QC25 headphones. Three product-specific dummies (*GoPro Black*, *GoPro Silver*, *GoPro Session*) represent the models of GoPro cameras. *Standard Xbox* represents the original Xbox One console and the remaining, fourteen, dummies represent special edition Xbox models.

The special edition models often paired the Xbox with newly released games, included unique "skins" for the console, and had upgraded hard drives. For example, the Xbox "Day One" edition includes a commemorative controller and premium packaging, and the Xbox One 1 TB edition includes an upgraded hard drive. For more information on the bundles and special edition models, see Ap. B., which lists the

contents of every special edition package, the manufacturer suggested retail price (MSRP), and the manufacturer-designed identifiers used to sort the listings by product.

Table 3 lists the most common special edition Xbox models in alphabetical order. The most common is the Halo Master Chief edition, with 1,105 observations. This represents 30.41% of the observations involving a special edition and 13.23% of the entire sample (N=8,351). The second most common special edition is the Assassin's Creed Unity (*Assassin's Creed*) edition, representing 22.37% of the special editions and 9.74% of the overall sample.

Two additional product-related controls are included to control for common features of the special edition models. *Kinect* equals one if the Kinect sensor is included in the listing, and *One TB HDD* equals one if an upgraded, One Terabyte (TB) hard drive (HDD) is included. As shown in Ap. B, three of the special editions (Assassin's Creed, Day One, Master Chief) include the Kinect and nine (COD:AW, Elite, Fallout 4, Fifa 16, Forza 6, Halo Guardians, Madden NFL 2015, Master Chief, Tomb Raider) include an upgraded hard drive. Note that the Assassin's Creed edition was also offered without the Kinect and the Master Chief edition was offered without the Kinect or One TB HDD, and these dummies account for these circumstances.

Table 3: Xbox Model Identifiers and Frequencies

Xbox Model	MPN	Freq.	% Xbox	% Total
Standard	7UV-00077	714	19.65%	8.55%
Assassin's Creed	5C7-00042	813	22.37%	9.74%
COD: AW	5C7-00075	22	0.61%	0.26%
Day One	7UV-0005	31	0.85%	0.37%
Elite	TM3-00002	14	0.39%	0.17%
Fallout 4	KG4-00026	20	0.55%	0.24%
Fifa 16	KF7-00043	55	1.51%	0.66%
Forza 6	KF6-00053	186	5.12%	2.23%
Gears of War	5C5-00081	320	8.81%	3.83%
Halo Guardians	KF6-00058	62	1.71%	0.74%
Lego Movie	5C7-00143	29	0.80%	0.35%
Madden NFL 2016	KF6-00064	245	6.74%	2.93%
Master Chief	5C6-00017	1,105	30.41%	13.23%
Sunset Overdrive	6QZ-00026	4	0.11%	0.05%
Tomb Raider	KF7-00044	14	0.39%	0.17%
		3,634		N=8,351

Note: After trimming *Landed Price* and *Time to Sale* at the 5% and 95% levels

Two additional product-related controls capture the time since the launch of the product (*Weeks from Launch* and *Preorder*). *Weeks from Launch* represents the weeks between the launch of the product/special edition and the sale. *Preorder* controls for sales occurring prior to product launch. *Weeks from Launch* equals zero for all preorders.

Table 4 lists the products by release date and displays the average *Weeks from Launch* and percentage of *Preorders*. The *Standard Xbox* and the special edition "*Day One*" model were released on November 22, 2013, making them the "oldest" products

in the sample. All three Bose models were released on September 3, 2014. The "youngest" product in the sample is the *Elite* edition Xbox, which debuted on December 1, 2015. Since, the data collection process concluded on November 11, 2015, all the listings for the *Elite* model are preorders.

Not surprisingly, the *Lego Movie* and *Day One* models, two of the three oldest products in the sample, had the longest *Weeks from Launch* and no preorders. This contrasts with the two most recent products, the *Elite* model, which only included preorders, and the *Fallout 4* model, which was preordered 10% of the time and had an average *Weeks from Launch* of only 0.88 (6.16 days).

Table 4: Product Release Dates, Weeks from Launch, and Preorders

Product	Release Date	Weeks from Launch	Preorders
Standard with Kinect	11/22/2013	29.70	0%
Day One	11/22/2013	83.10	0%
Lego Movie	2/7/2014	90.80	0%
Standard without Kinect	6/9/2014	28.07	0%
Bose Black	9/3/2014	50.23	0%
Bose Custom	9/3/2014	56.67	0%
Bose White	9/3/2014	47.90	0%
GoPro Black	9/29/2014	37.58	0%
GoPro Silver	9/29/2014	39.08	0%
Sunset Overdrive	10/28/2014	25.45	0%
COD: AW	11/3/2014	25.96	0%
Master Chief	11/11/2014	37.50	0%
Assassin's Creed	11/11/2014	27.02	0%
GoPro Session	7/12/2015	10.33	0%
Gears of War	8/25/2015	7.30	2%
Madden NFL 2016	8/25/2015	6.17	6%
Forza 6	9/15/2015	2.56	21%
Fifa 16	9/22/2015	4.20	0%
Halo Guardians	10/20/2015	1.99	27%
Tomb Raider	11/3/2015	1.66	0%
Fallout 4	11/10/2015	0.88	10%
Elite	12/1/2015	0.00	100%
Average		27.92	1%

Empirical Model Specification

To test the hypotheses, the following system of equations is estimated:

$$\text{Log Landed Price} = f\{\textit{ReturnPolicy}, \textit{TransactionRelatedControls}, \textit{SellerRelatedControls}, \textit{ProductRelatedControls}\}$$

$$\text{Time to Sale} = f\{\textit{LandedPrice(fitted)}, \textit{ReturnPolicy}, \textit{TransactionRelatedControls}, \textit{SellerRelatedControls}, \textit{ProductRelatedControls}\}$$

A three-stage least squares (3SLS) procedure is used to include a fitted value of the *Landed Price* in the demand equation. This two-equation system estimates the impact

of the return policy from both the seller- and market-perspectives. By comparing the impact of the return policy on the *Landed Price* and the *Time to Sale*, the monetary value of each return policy parameter is determined, and the focus of the two sets of marketplace participants is compared.

The first equation represents the supply-side of the system, with the seller setting the *Landed Price* based on the product and listing characteristics, their return policy, their reputation in the marketplace, and any remaining details of the transaction. The transaction characteristics include: the length of the product description (*Description Length*), the number of images provided (*Images*), the percentage of the landed price attributed to shipping and handling (*Percent Ship Charge),* and whether the quantity of previously sold, identical units is displayed (*Previously Sold*).

The seller characteristics include tenure on eBay (*Seller Tenure*) and online reputation as judged by numerical feedback ratings over the previous year (*Percent Positive, Percent Negative, Log Positive, Log Negative-Neutral*). The seller also determines the price based on the characteristics of the product(s); so, twenty product-specific dummy variables are included to control for deviations across the base products and special edition models. The trend in demand is captured with a measure of the weeks since the products' release (*Weeks from Launch*), and *Preorder* accounts for sales occurring before the product launch.

The demand-side of the system is represented by the second equation, with the *Time to Sale* reflecting the market's reaction to the terms of the listing. The market is expected to react to the landed price of the product, the return policy, the presentation of the product, and the seller characteristics. Lower *Time to Sale* is assumed to correspond to higher demand.

Four models are estimated with different combinations of return policies and seller reputation measures. Model 1 controls for seller reputation with the percentage of positive (*Percent Positive)* and negative (*Percent Negative)* feedback ratings over the previous year. The percentage of neutral ratings is left out to avoid perfect multicollinearity. Four return policy components are included in model 1: *Shorter Window, Default Window, Extended Window, Free Return Shipping, Free Shipping,* and *Restocking Fee.* Thus, model 1 includes the following equations:

$$\text{Log Landed Price} = f\{ShorterWindow,\ DefaultWindow,\ ExtendedWindow,\ FreeReturnShipping, FreeShipping, RestockingFee,\ TransactionRelatedControls, PercentPositive,\ PercentNegative, ProductRelatedControls\}$$

$$\text{Time to Sale} = f\{LandedPrice(fitted), ShorterWindow,\ DefaultWindow,\ ExtendedWindow, FreeReturnShipping, FreeShipping,\ RestockingFee, TransactionRelatedControls,\ PercentPositive, PercentNegative, ProductRelatedControls\}$$

Model 2 includes the same seller reputation measures and return policy components as model 1, except *Restocking Fee* (a catchall for any restocking fee) is replaced with four restocking fee measures: *Restock 10%, Restock 15%, Restock 20%,* and *Restock Other.* The complete sample is used to estimate model 1 and model 2, which includes the following equations:

Log Landed Price = f {*ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, Restock10%, Restock15%, Restock20%, RestockOther, TransactionRelatedControls, PercentPositive, PercentNegative, ProductRelatedControls*}

Time to Sale = f {*LandedPrice(fitted), ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, Restock10%, Restock15%, Restock20%, RestockOther, TransactionRelatedControls, LogPositive, LogNeutral - Negative, ProductRelatedControls*}

Model 3 replaces the percentage reputation measures with the logged count of positive and negative/neutral ratings. Thus, *Log Positive* and *Log Negative-Neutral* are included to control for seller reputation. These are the most common reputation measures included in the empirical research using eBay data (Cabral and Hortacsu, 2010; Resnick and Zeckhauser, 2002; Subramanian and Subramanyam, 2012; Shang et al., 2017b). The same set of return policy components used in model 1 are included in model 3, which takes the following form:

Log Landed Price = f {*ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, RestockingFee, TransactionRelatedControls, LogPositive, LogNeutral - Negative, ProductRelatedControls*}

Time to Sale = f {*LandedPrice(fitted), ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, Restock10%, Restock15%, Restock20%, RestockOther, TransactionRelatedControls, LogPositive, LogNeutral - Negative, ProductRelatedControls*}

The final model (4) includes the logged reputation measures – *Log Positive, Log Negative-Neutral* – and the set of return policy components used in model 2 – *Shorter*

Window, Default Window, Extended Window, Free Return Shipping, Restock 10%, Restock 15%, Restock 20%, and *Restock Other*.

Since the count of positive and negative-neutral ratings in models 3 and 4 are logged, sellers without any such ratings are dropped from the analysis. The sample includes a diverse set of sellers, and many do not have any negative or neutral ratings during the observed period. Therefore, the sample used to estimate models 3 and 4 is limited to 5,174 observations. The equations for model 4 follow.

$$\text{Log Landed Price} = f\{ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, Restock10\%, Restock15\%, Restock20\%, RestockOther, TransactionRelatedControls, LogPositive, LogNeutral - Negative, ProductRelatedControls\}$$

$$\text{Time to Sale} = f\{LandedPrice(fitted), ShorterWindow, DefaultWindow, ExtendedWindow, FreeReturnShipping, FreeShipping, Restock10\%, Restock15\%, Restock20\%, RestockOther, TransactionRelatedControls, LogPositive, LogNeutral - Negative, ProductRelatedControls\}$$

ESTIMATION AND RESULTS

In this section, the results of the correlation and regression analysis are presented. Due to the large number of variables in the analysis, the results are spread across four sub-sections. First, the correlation matrix is presented, and the coefficients are interpreted. Next, the regression results for the control variables are discussed. To avoid problems with omitted variable bias, these results are extracted from the most predictive regression model (model 2). Then, the supply-side (first equation) regression results are interpreted, demonstrating the monetary value that the sellers place on each

return policy parameter. Finally, the results of the demand-side (second equation) regressions are presented and the significant factors are compared to those in the supply-side regressions. This process presents the results from both the buyer- and seller- perspective and the analysis reveals differences in their perceived value of various return policy components. The three sets of control variables (transaction-related, seller-related, product-related) are included in all models, and StataMP (version 15.1) is used for estimation. The unadjusted coefficients (β-values) are listed along with the t-values in parentheses.

Correlation Analysis

Table 5 presents the pairwise correlations for the primary variables of interest. A full correlation matrix including all variables appears in Appendix E. As indicated by the stars in table 5, most correlations are statistically significant at the 5% level. This is expected due to the large sample size. Few correlations, however, are larger than 0.50.

As expected, *Landed Price* and *Hours to Sale* are positively correlated, with a correlation coefficient of 0.17. Since *Hours to Sale* is inversely related to demand, this positive coefficient confirms the Law of Demand. In line with the hypotheses presented earlier, *Extended Window* and *Free Return Shipping* are highly correlated with both *Landed Price* and *Hours to Sale*. Similarly, all five restocking fee measures are highly correlated with *Hours to Sale*, with coefficients ranging from 0.06 to 0.32. Surprisingly,

the catchall *Restocking Fee* and *Restock 20%* are also positively correlated with *Landed Price,* and *Default Window* is uncorrelated with *Landed Price* at the 5% level.

Several relationships amongst the variables of interest are also worth noting. A positive and significant correlation is found between *Free Shipping* and the use of both the *Default Window* and *Extended Window*. However, a negative correlation is found between *Free Return Shipping* and *Default Window*, while the relationship between *Free Return Shipping* and *Extended Window* is positive. The coefficient of 0.46 between *Free Return Shipping* and *Extended Window* indicates that those two lenient return policy components are likely to be used in conjunction. In general, restocking fees are also positively correlated with the *Default Window* and the *Extended Window*, with coefficients of 0.32 and 0.05, respectively. No correlation is found for *Shorter Window* with any of the other eleven variables.

Table 5: Correlation Matrix for Variables of Interest

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Landed Price	1											
2	Hours to Sale	0.17*	1										
3	Shorter Window	0.01	-0.007	1									
4	Default Window	0.00	0.05*	-0.01	1								
5	Extended Window	0.03*	0.07*	0.00	-0.18*	1							
6	Free Shipping	0.00	0.01	0.01	0.12*	0.07*	1						
7	Free Return Shipping	0.06*	0.05*	0.00	-0.06*	0.46*	0.05*	1					
8	Restocking Fee	0.03*	0.10*	-0.01	0.32*	0.05*	0.11*	0.01	1				
9	Restock 10%	0.01	0.04*	0.00	0.15*	0.09*	0.04*	0.01	0.53*	1			
10	Restock 15%	0.00	0.06*	0.00	0.14*	0.03*	0.04*	0.00	0.43*	-0.02*	1		
11	Restock 20%	0.03*	0.06*	0.00	0.24*	-0.03*	0.09*	0.01	0.67*	-0.04*	-0.03*	1	
12	Restock Other	0.01	0.04*	0.00	0.06*	-0.01	0.01	-0.01	0.17*	-0.01	-0.01	-0.01	1

Note: N = 8351 and * indicates significance at the 5% level

Results for the Control Variables

Prior to assessing the size and significance of the variables of interest, the regression results for the controls are evaluated. This validates the empirical specification, addresses concerns of omitted variable bias, and sets the stage for the primary analysis. Table 6 presents the results for the control variables included in the full (most predictive) regression model (Model 2). The first column presents the results of the first equation, with *Log Landed Price* as the dependent variable and the full set of control and independent variables as regressors. The second column presents the second equation results, with *Hours to Sale* as the dependent variable and the full set of controls, independent variables, and fitted value of *Landed Price* as regressors.

The R^2 values of both models are 0.8461 and 0.1658 in the *Landed Price* and *Hours to Sale* equations, respectively, indicating that a substantial proportion of the variance is explained by this set of variables. In general, the results make intuitive sense and align with prior studies. The following subsections discuss the results of the transaction-, seller-, and product-related controls.

Table 6: Control Variable Results for Regression Model 2

Base = Bose White	DV = Log Landed Price Model 2 β (t)		DV = Hours to Sale Model 2 β (t)	
Constant	5.5770***	(646.91)	-230.6888***	(-17.43)
Description Length	-0.0004	(-0.64)	3.7742***	(5.87)
Images	0.0034***	(10.72)	2.3142***	(6.55)
Percent Ship Charge	0.3815***	(7.25)	7.8218	(0.13)
Previously Sold	0.0027*	(1.77)	33.7154***	(19.62)
Weeks from Launch	-0.0017***	(-23.49)	0.5650***	(6.56)
One TB HDD	0.1115***	(22.99)	-30.9643***	(-5.53)
Kinect	0.2346***	(58.89)	-64.5161***	(-12.10)
Preorder	-0.0513***	(-6.19)	13.0698	(1.40)
Seller Tenure	0.0004***	(2.92)	-0.2676	(-1.64)
Percent Positive	0.0095	(1.56)	8.9898	(1.31)
Percent Negative	-0.1239***	(-8.51)	-20.347	(-1.24)
Assassin's Creed	0.2415***	(46.94)	-50.8731***	(-8.23)
Bose Black	0.0151***	(2.99)	-20.6466***	(-3.64)
Bose Custom	0.0598***	(7.78)	-15.8466*	(-1.83)
COD: AW	0.3183***	(21.29)	-70.9428***	(-4.15)
Day One	0.3459***	(27.70)	-54.7830***	(-3.79)
Elite	0.4892***	(24.33)	-143.3472***	(-6.17)
Fallout 4	0.2779***	(17.37)	-69.3429***	(-3.82)
Fifa 16	0.2512***	(22.27)	-23.9893*	(-1.87)
Forza 6	0.2569***	(28.61)	-76.5726***	(-7.40)
Gears of War	0.2111***	(32.78)	-45.8481***	(-6.16)
GoPro Black	0.4926***	(107.12)	-113.9609***	(-15.38)
GoPro Session	0.2519***	(39.08)	-30.1575***	(-3.98)
GoPro Silver	0.3146***	(69.59)	-62.0737***	(-10.48)
Halo Guardians	0.4673***	(41.61)	-131.1045***	(-9.58)
Lego Movie	0.3677***	(28.90)	-70.1440***	(-4.75)
Madden NFL 2016	0.2420***	(28.27)	-57.7204***	(-5.86)
Master Chief	0.2943***	(61.11)	-59.4960***	(-9.74)
Standard Xbox	0.2878***	(54.01)	-60.2681***	(-9.12)
Sunset Overdrive	0.5992***	(19.01)	-146.7107***	(-4.07)
Tomb Raider	0.2469***	(13.36)	-64.9918***	(-3.12)
Return Policy	Included		Included	
R^2:	0.8370		0.1477	
Observations:	8351		8351	

* p<0.10, ** p<0.05, *** p<0.01

Results of the Transaction-Related Controls

Description Length, which is measured in thousands of characters, is shown to have an insignificant impact on *Landed Price*. Since, many sellers simply copy and paste their product descriptions from other listings or retailers, it is not surprising that they place little weight on this component of the transaction while determining the landed price. Surprisingly, *Description Length* is positively associated with *Time to Sale*. As shown in table 6, a 1,000-character increase in the description length is associated with an approximate 3.8-hour delay in the time to sale.

Images on the other hand, are shown to be positively related to *Landed Price*. Due to the ease of adding images on eBay, many sellers opt to include images of the actual item for sale, instead of using relying on manufacturer provided stock images. The results suggest that sellers incorporate the uncertainty reduction from these images into the prices they charge, with each additional image raising the *Landed Price* by 0.34%. However, the results also show that *Images*, similar to *Description Length*, are positively related to *Time to Sale*. Each additional image is associated with an approximate 2.3-hour delay in the time to sale.

Percent Ship Charge accounts for the percentage of the landed price attributed to shipping and handling and is positively associated with *Landed Price*. That is, the more expensive the shipping and handling relative to the product, the higher the overall landed price. No relationship is found between *Percent Ship Charge* and *Hours to Sale.*

Previously Sold is equal to one if the quantity of previously sold units is displayed on the listing page. Only units with identical characteristics are included in the count. Thus, the previous units must have been sold by the same seller, in the "fixed price" format, with an identical product description, and the same set of images. The price can vary slightly, however, too many price adjustments or too large of a price swing, will result in the creation of new listing ID and count measure. The results in table 6 reveal that sellers build this information into their price; however, it only increases *Landed Price* by approximately 0.27%.

Results of the Seller-Related Controls

Model 2 includes three variables related to seller characteristics: the time between the creation of the seller ID and the sale (*Seller Tenure)*, the percentage of the seller's feedback ratings that are positive twelve months prior to the sale (*Percent Positive*), and the percentage of ratings that are negative twelve months prior (*Percent Negative*).

A positive association is found between *Seller Tenure* and *Landed Price*, indicating that sellers capitalize on their experience on eBay by charging higher landed prices. *Seller Tenure* is marginally significant in the *Time to Sale* regressions, with p-values of -1.64 and p-values of 0.099 and 0.1004 in models 1 and 2, respectively. However, it is practically insignificant, with model 2 demonstrating an additional year of experience resulting in only a 0.27-hour reduction in the time to sale.

Results of the Product-Related Controls

Weeks from Launch controls for changes in demand across product lifecycles. As expected, the coefficient on *Weeks from Launch* is negative and significant in the supply regression and positive and significant in the demand regression. This confirms that the landed price diminishes and the demand for the product decreases with the time since the product launch. The *Landed Price* is shown to drop by approximately 0.17% every week post release, and the product takes approximately 34 minutes longer to sell with each additional week it is on the market.

The *Kinect* and *One TB HDD* variables separately control for the inclusion of the Kinect sensor and an upgraded (1 TB) hard drive (HDD) in Xbox listings. As expected, these additional features result in higher *Landed Price* compared to the standard Xbox model. *Kinect* and *One TB HDD* also result in lower *Time to Sale,* which demonstrates higher demand for these more exclusive and higher priced items.

The results reveal that *Preorders*, sales occurring prior to product launch, are associated with 5.13% lower *Landed Price,* which confirms expectations. Sellers offer preorders to gain an understanding of future demand and to avoid competition on the release date. For this information, sellers are willing to accept a slightly lower landed price. No association is found between *Preorder* and *Hours to Sale.* That is, demand is not heavily influenced by the assurance of supply in this setting.

The product with the lowest average price, the (white) Bose QC25 headphones, was selected as the base and twenty product-specific dummies were included in each

equation to account for price and demand differences across products and special editions. As shown in table 6, all forty variables are significant in Model 2. Thus, the coefficients on the product-specific controls in the first column can be interpreted as the price differential between the listed product and the (white) Bose QC25 headphones. Similarly, the product-specific coefficients in the second column represent differences in demand between the product and the (white) Bose QC25 headphones.

Overall, the regression results for the control variables confirm expectations and provide strong assurance against omitted variable bias. Differences in supply and demand are controlled for with a large set of transaction-, seller-, and product-specific factors.

Table 7: Results for Regression Models 1 and 2

	Log Landed Price				Hours to Sale			
	Model 1		Model 2		Model 1		Model 2	
	β (t)		β (t)		β (t)		β (t)	
Constant	5.5766***	(646.64)	5.5770***	(646.91)	-231.5329***	(-17.50)	-230.6888***	(-17.43)
Description Length	-0.0002	(-0.37)	-0.0004	(-0.64)	3.8699***	(6.05)	3.7742***	(5.87)
Images	0.0034***	(10.71)	0.0034***	(10.72)	2.3150***	(6.55)	2.3142***	(6.55)
Percent Ship Charge	0.3794***	(7.21)	0.3815***	(7.25)	6.7780	(0.11)	7.8218	(0.13)
Previously Sold	0.0026*	(1.72)	0.0027*	(1.77)	33.7044***	(19.63)	33.7154***	(19.62)
Weeks from Launch	-0.0017***	(-23.58)	-0.0017***	(-23.49)	0.5620***	(6.53)	0.5650***	(6.56)
Seller Tenure	0.0004***	(2.87)	0.0004***	(2.92)	-0.2682*	(-1.65)	-0.2676	(-1.64)
Percent Positive	0.0095	(1.55)	0.0095	(1.56)	8.9477	(1.31)	8.9898	(1.31)
Percent Negative	-0.1243***	(-8.53)	-0.1239***	(-8.51)	-20.4506	(-1.25)	-20.347	(-1.24)
Shorter Window	0.1522***	(3.44)	0.1528***	(3.45)	-90.5619*	(-1.82)	-90.0646*	(-1.81)
Default Window	0.0018	(1.15)	0.0019	(1.21)	-1.1957	(-0.66)	-1.1316	(-0.63)
Extended Window	0.0125***	(2.95)	0.0138***	(3.22)	4.7271	(0.99)	5.4387	(1.13)
Free Shipping	0.0076***	(2.72)	0.0077***	(2.75)	-1.4856	(-0.47)	-1.4465	(-0.46)
Free Return Shipping	-0.0107	(-1.54)	-0.0112	(-1.60)	6.5215	(0.84)	6.3246	(0.81)
Restocking Fee	0.0041	(1.61)			9.8742***	(3.41)		
Restock 10%							4.2239	(0.88)
Restock 15%			0.0086	(1.63)			14.0900**	(2.39)
Restock 20%			0.0076**	(2.14)			10.8417***	(2.71)
Restock Other			0.0187	(1.48)			25.6313*	(1.80)
Landed Price					0.7750***	(23.43)	0.7730***	(23.36)
Product Controls	Included		Included		Included		Included	
R^2:	0.8368		0.8370		0.1474		0.1477	
Observations	8351		8351		8351		8351	

* p<0.10, ** p<0.05, *** p<0.01

Return Policies and Landed Price

The left-half of Table 7 presents the supply-side results for the primary variables of interest as well as the transaction- and seller-related controls for interpretation purposes. The twenty-four product-related controls are also included in both models but are not displayed due to space limitations. The first column (Model 1) includes a dummy variable, *Restocking Fee,* which takes the value of one if any restocking fee is mentioned on the listing page or in the seller's written return policy and zero otherwise. The second column (Model 2) disaggregates the restocking fees into four categories, representing restocking fees of 10% (*Restock 10%)*, 15% (*Restock 15%*), 20% (*Restock 20%*), and all other percentages (*Restock Other)*. The base case is a no-returns-allowed policy, and all of the results demonstrate the impact of deviating from this policy.

The results reveal a surprisingly insignificant relationship between return allowance with the default, two-week return window (*Default Window*) and *Landed Price.* This result holds in both regressions. This is not to say that there is no value in allowing returns, but it does indicate that these sellers do not expect to earn a price premium for utilizing the default return window. The coefficients for *Shorter Window* and *Extended Window* are highly significant and positive, however. Since the regression model is log-linear and *Extended Window* is a dummy variable, representing return allowance with a return window greater than the default, this coefficient can be interpreted as the percentage increase in the landed price associated with this decision. Thus, the coefficient of 0.0138 indicates that a 1.38% increase in *Landed Price* is associated with a return window greater than 14 days relative to a no returns policy.

This supports **Hypothesis 1**. With an average *Landed Price* per unit (across all products) of $358, this equates to an approximate $4.94 increase in *Landed Price*. Similarly, a return window less than the default (*Shorter Window*), is associated with a 15.28% or $54.70 increase in *Landed Price*, on average. The magnitude of this impact is surprising; however, it suggests the value of deviations away from the institutional norm (i.e. the default return window). Since, this effect is limited to only five observations, further examination of this variable is better suited to future research. The significance and magnitude of all parameters of interest remain unchanged when these five observations are omitted.

Counter to **Hypothesis 1,** a lack of association is found between *Landed Price and Free Return Shipping*, and in the aggregate, restocking fees are not found to significantly impact *Landed Price.* Thus, **Hypothesis 1** is only partially supported.

Finally, *Free Shipping* is found to have a positive and highly significant impact on *Landed Price*. The coefficient of 0.0077 suggests that *Landed Price* increases by .077% when shipping is free of charge. Thus, customers are willing to pay $2.76 more, on average, to avoid non-refundable (sunk) shipping charges, which would be lost if the product was returned. This result supports **Hypothesis 2.**

Return Policies and Time to Sale

The results of the demand-side regression models are displayed on the right-half of table 7. *Time to Sale* is measured in hours (*Hours to Sale*) trimmed at the 5% level.

Model 1, in the first column, includes an aggregate, dummy variable capturing the presence of any restocking fee, whereas model 2, in the final column, includes four disaggregate measures corresponding to restocking fees of 10%, 15%, 20%, and any other percentage. Transaction-, seller-, and product-related controls are included in both models as is *Landed Price* in its unadjusted (linear) form.

As mentioned earlier, *Time to Sale* is used to represent the demand for a listing and its characteristics. The quicker the *Time to Sale*, the higher the demand for the listing. Thus, after controlling for the *Landed Price* and the other terms of sale, a negative coefficient indicates a higher demand for the listing. The coefficient on *Landed Price* is positive and highly significant in all three models, in alignment with the Law of Demand. That is, the higher the price, the lower the demand for the listing, and the longer it takes to sell the product(s). The coefficient for *Landed Price* in model 2 is 0.7730, indicating that a $1 increase in *Landed Price* is associated with a 0.7730-hour delay of the sale.

Surprisingly, the coefficients for both *Default Window* and *Extended Window* are insignificant in the *Time to Sale* equation. Meanwhile, the coefficient for *Shorter Window* is negative and highly significant. This once again supports the benefits of deviating from the default return policy; however, it is once again a function of very few (5) observations. Thus, this result is likely due to extreme outliers, and due to the very few observations in this category, and as a result is best suited to future research.

Counter to **Hypothesis 3**, *Free Return Shipping* is found to have an insignificant impact on the *Time to Sale,* indicating that consumers do not react strongly to this signal. This result is consistent with the seller-perspective measure in the *Landed Price* equation.

Restocking Fee is positive and highly significant in both its aggregate and disaggregate forms, supporting **Hypothesis 3**. Column three demonstrates that a restocking fee of any form is associated with a 9.87-hour increase in the *Time to Sale*. Furthermore, as shown in the final column, the impact of restocking fees is nonlinear, with the impact differing according to the percentage and type of restocking fee. No association is found between a restocking fee of 10% and *Time to Sale* compared to a no-restocking fee policy. However, restocking fees of 15% and 20% are associated with approximately 14.1- and 10.84-hour increases in *Time to Sale*, respectively.

Interestingly, the largest delay in *Time to Sale* is associated with restocking fees outside of the standard options (10%, 15%, 20%). These non-standard restocking fees could be very large percentages of the product price, equal to the shipping charges, specific dollar values, or completely unspecified values. The common element amongst these non-standard fees (*Restock Other*) is that they require additional effort on the buyer to locate and comprehend. The coefficient for *Restock Other* is positive and highly significant. The coefficient for this variable of 25.6313 indicates that *Time to*

Sale is prolonged by approximately 25.63 hours when one of the non-standard restocking fees are utilized.

Alternative Specifications

To ensure that the results are robust against alternative seller reputation measures, two additional models (3 and 4) are estimated. These models include the same set of regressors as models 1 and 2, respectively; however, they include logged measures of seller reputation. *Log Positive* is the natural logarithm of the total positive feedback ratings received by the seller 12 months prior to the sale. *Log Neutral-Negative* is the natural logarithm of the total neutral or negative feedback ratings received by the seller 12 months prior to the sale. The results for the control variables in models 4 are presented in table 8, and the primary regression results with these two alternative seller reputation measures are presented in table 9.

Since many sellers, do not have any neutral or negative ratings in the 12 months preceding their sale, the logarithmic transformation is impossible, and therefore the transactions involving these sellers are omitted from the analysis. From the sample truncated at the 5% level, 118 observations involve sellers without any positive feedback ratings twelve months prior to the sale, 4,393 involve sellers without any neutral ratings, and 4,247 involve sellers without any negative ratings. 3,167 involve sellers without any neutral or negative ratings and 108 involve sellers without any ratings of any kind twelve months prior to sale. The omission of these observations results in a useable sample size of 5,174.

Surprisingly, models 3 and 4 are more predictive, based on the R^2 values, than models 1 and 2, despite the smaller sample size. With values of 0.8638 and 0.8641 in the first equation and 0.1655 and 0.1658 in the second equation for models 3 and 4, respectively, the R^2 values are high, indicating that a substantial proportion of the variance in the dependent variable is explained by these empirical specifications.

The results for the control variables in model 4 (see table 8) are very similar to the results for model 2 (see table 6), and the signs and significance levels for all variables remain the same except for two variables. The sign and significance of all product controls is consistent across the two models. Preorder is positive and significant in the *Time to Sale* equation in model 4 (p-value = 0.0741), whereas it is positive and insignificant in model 2 (p-value = 0.1602). *Seller Tenure* is insignificant in the *Landed Price* equation in model 4, whereas it is positive but practically insignificant in model 2. Meanwhile, *Seller Tenure* is negative and significant in model 4, but insignificant in model 2. Finally, the logged seller-reputation measures appear to explain more of the variance in *Landed Price* and *Time to Sale* than the percentage measures. *Log Positive* and *Log Neutral-Negative* are significant in both the *Landed Price* and *Time to Sale* equations, while *Percent Positive* is insignificant in both equations and *Percent Negative* is only significant in the *Landed Price* equation. Despite these differences, the results remain largely unchanged with this alternative specification, providing further evidence towards the research hypotheses.

Table 8: Control Variable Results for Regression Model 4

Log Landed Price	DV = Log Landed Price Model 4 β (t)		DV = Hours to Sale Model 4 β (t)	
Constant	5.5701***	(691.35)	-284.1700***	(-17.58)
Description Length	-0.0003	(-0.45)	5.6172***	(6.65)
Images	0.0022***	(6.17)	1.8207***	(4.08)
Percent Ship Charge	0.5490***	(6.54)	25.5343	(0.24)
Previously Sold	0.0056***	(3.20)	33.4587***	(15.39)
Weeks from Launch	-0.0017***	(-19.78)	0.5802***	(5.11)
One TB HDD	0.1202***	(21.67)	-36.8064***	(-5.13)
Kinect	0.2448***	(50.90)	-74.4999***	(-10.13)
Preorder	-0.0598***	(-6.59)	20.2038*	(1.79)
Seller Tenure	-0.0000	(-0.04)	-0.4944**	(-2.15)
Log Positive	0.0047***	(5.87)	2.8348***	(2.82)
Log Neutral-Negative	-0.0088***	(-9.57)	2.5815**	(2.24)
Assassin's Creed	0.2352***	(39.83)	-60.7219***	(-7.65)
Bose Black	0.0101*	(1.79)	-19.4577***	(-2.78)
Bose Custom	0.0560***	(6.95)	-17.8112*	(-1.77)
COD: AW	0.3367***	(18.68)	-57.5756**	(-2.51)
Day One	0.3587***	(18.96)	-83.6193***	(-3.47)
Elite	0.4781***	(22.61)	-164.8499***	(-6.02)
Fallout 4	0.2725***	(15.78)	-84.1782***	(-3.87)
Fifa 16	0.2374***	(19.13)	-39.5574**	(-2.52)
Forza 6	0.2337***	(22.74)	-86.2123***	(-6.58)
Gears of War	0.2081***	(26.93)	-49.0695***	(-4.95)
GoPro Black	0.4793***	(90.47)	-128.8414***	(-13.07)
GoPro Session	0.2352***	(31.40)	-29.6729***	(-3.04)
GoPro Silver	0.3088***	(59.66)	-67.3063***	(-8.73)
Halo Guardians	0.4536***	(35.05)	-159.8881***	(-9.05)
Lego Movie	0.3547***	(26.17)	-79.9763***	(-4.54)
Madden NFL 2016	0.2273***	(22.75)	-72.0096***	(-5.66)
Master Chief	0.2770***	(48.96)	-64.3623***	(-8.08)
Standard Xbox	0.2711***	(43.62)	-61.5367***	(-7.19)
Tomb Raider	0.2545***	(11.25)	-62.1593**	(-2.20)
Return Policy	Included		Included	
R^2:	0.8641		0.1658	
Observations:	5174		5174	

* p<0.10, ** p<0.05, *** p<0.01

Table 9: Results for Regression Models 3 and 4

	Model 3 β (t)		Model 4 β (t)		Model 3 β (t)		Model 4 β (t)	
Constant	5.5692***	(691.17)	5.5701***	(691.35)	-284.7472***	(-17.65)	-284.1700***	(-17.58)
Description Length	-0.0001	(-0.08)	-0.0003	(-0.45)	0.8940***	(19.03)	0.8934***	(18.99)
Images	0.0022***	(6.11)	0.0022***	(6.17)	5.6598***	(6.74)	5.6172***	(6.65)
Percent Ship Charge	0.5497***	(6.55)	0.5490***	(6.54)	1.8407***	(4.13)	1.8207***	(4.08)
Previously Sold	0.0055***	(3.13)	0.0056***	(3.20)	25.1558	(0.24)	25.5343	(0.24)
Weeks from Launch	-0.0018***	(-19.96)	-0.0017***	(-19.78)	33.5739***	(15.48)	33.4587***	(15.39)
Seller Tenure	0.000	(-0.02)	0.0000	(-0.04)	0.5814***	(5.13)	0.5802***	(5.11)
Log Positive	0.0048***	(5.96)	0.0047***	(5.87)	-0.4771**	(-2.09)	-0.4944**	(-2.15)
Log Negative	-0.0089***	(-9.70)	-0.0088***	(-9.57)	2.7985***	(2.79)	2.8348***	(2.82)
Default Window	0.0044**	(2.24)	0.0046**	(2.31)	-7.8435***	(-3.18)	-7.7836***	(-3.16)
Extended Window	0.0226***	(5.15)	0.0237***	(5.38)	-8.8376	(-1.62)	-8.5904	(-1.57)
Free Shipping	0.0177***	(4.56)	0.0177***	(4.58)	-1.4605	(-0.30)	-1.36	(-0.28)
Free Return Shipping	0.003	(0.48)	0.0033	(0.45)	-16.7270*	(-1.88)	-16.5646*	(-1.86)
Restocking Fee	-0.001	(-0.24)			7.3736**	(2.17)		
Restock 10%			-0.0110**	(-2.47)			8.0205	(1.45)
Restock 15%			0.0074	(1.35)			3.5508	(0.52)
Restock 20%			0.0016	(0.44)			7.2966	(1.59)
Restock Other			0.0259*	(1.76)			30.2475*	(1.65)
Landed Price					0.8940***	(19.03)	0.8934***	(18.99)
Product Controls	Included		Included		Included		Included	
R2:	0.8638		0.8641		0.1655		0.1658	
Observations:	5174		5174		5174		5174	

* p<0.10, ** p<0.05, *** p<0.01

Note: Shorter Window omitted due to multicollinearity

The results of the alternative specification reveal a significant and positive relationship between return allowance with the default, two-week return window (*Default Window*) and *Landed Price.* This result holds in both regressions. Since the regression model is log-linear and *Default Window* is a dummy variable, representing return allowance with the default (14-day) return window, this coefficient can be interpreted as the percentage increase in *Landed* Price associated with this decision. Thus, the coefficient of 0.0046, in model 4, indicates that a 0.05% increase in the landed price is associated with the default return window relative to a no-returns-allowed policy. With an average *Landed Price* per unit (across all products) of $358, this equates to an approximate $1.79 increase in *Landed Price*.

Extended Window is also found to have a positive and highly significant impact on *Landed Price.* The coefficient of 0.0237, in model 4, indicates that a 2.37% increase in the landed price is associated with an extended return window relative to a no-returns-allowed policy. With an average *Landed Price* per unit (across all products) of $358, this equates to an approximate $8.49 increase in *Landed Price*. This supports **Hypothesis 1.**

Counter to **Hypothesis 1,** a lack of association is found between *Landed Price and Free Return Shipping*. This is not to say that there is no value in offering free return shipping, but it does indicate that these sellers do not expect to earn a price premium for doing so.

In its aggregate form, *Restocking Fee* is not found to significantly impact *Landed Price;* however, when disaggregate restocking measures are used, two interesting results emerge. In model 4, *Restock 10%* is negative and highly significant and *Restock Other* is positive and highly significant. The coefficient of -0.0110 for *Restock 10%* suggests that sellers reduce the *Landed Price* by approximately 1.10%, or $3.94, on average, when they charge restocking fees of 10%. Meanwhile, the coefficient of 0.0259 for *Restock Other* suggests that sellers charge approximately 2.59%, or $9.27 *more* when they use restocking fees other than the standard options. These results partially support **Hypothesis 1**.

Overall, the results partially support **Hypothesis 1**. Some lenient return policy components are associated with higher *Landed Price*. Sellers appear to focus on the length of the return window and, to a lesser degree, the presence of restocking fees when setting the landed price. *Free Return Shipping* does not appear to significantly impact their decision.

Finally, *Free Shipping* is found to have a positive and highly significant impact on *Landed Price*. The coefficient of 0.0177 suggests that *Landed Price* increases by 1.77% when shipping is free of charge. Thus, customers are willing to pay $6.34 more, on average, to avoid non-refundable (sunk) shipping charges, which would be lost if the product was returned. This result supports **Hypothesis 2.**

The right-half of table 7 presents the results for the second (demand) equation in models 3 and 4. In conjunction with the law of demand, the coefficient for *Landed Price* is positive and highly significant in both models. The coefficient in model 4 is 0.8934, indicating that a $1 increase in *Landed Price* is associated with a 0.8934 hour delay of the sale.

The results in table 7 support **Hypothesis 3:** lenient return policies increase the demand for listings and reduce *Time to Sale***.** The coefficient for *Default Window* in the full model (4; final column) is -7.7836, indicating that allowing returns and using the default, 14-day return window results in an approximate 7.78-hour reduction in *Time to Sale*. The results appear to suggest that an even larger reduction in the *Time to Sale* can be achieved with an extended return window; however, the coefficient of -8.5904 in model 4 is insignificant, potentially due to the small number of observations in this category.

The coefficient on *Free Return Shipping* is -16.5646 and highly significant. This suggests that the removal of return shipping charges increases the demand for a listing and reduces *Time to Sale* by approximately 16.57 hours. This offers further support for **Hypothesis 3**.

The restocking fee measures are positive and highly significant in both models. Model 3 demonstrates that a restocking fee of any form is associated with a 7.37-day increase in *Time to Sale*. Furthermore, as shown in the final column, the impact of the

fees varies by restocking fee percentage and type. The coefficients for the standard restocking fees of 10%, 15%, and 20% are all positive, however they are statistically insignificant at the 10th level. However, restocking fees other than these standard options are associated with delays of approximately 30.25 hours before sale. These results support **Hypothesis 3**.

Summary of Results

The results of the hypothesis tests are summarized in table 10. Both specifications fully confirm hypothesis 2 and partially support hypotheses 1 and 3. Models 1 and 2 do not find a significant association between *Free Return Shipping* and *Time to Sale* but do find a significant association between restocking fees of 15% and 20% and *Time to Sale*.

Table 10: Summary of Hypothesis Test Results

Hypothesis	Independent Variable	Dependent Variable	Percentage Measures	Logged Measures
1	Lenient Return Policies	Landed Price	Partially Supported	Partially Supported
1a	Return Window	Landed Price	Significant	Significant
1b	Free Return Shipping	Landed Price	Insignificant	Insignificant
1c	Restocking Fees	Landed Price	Insignificant	Insignificant
2	Free Shipping	Landed Price	Supported	Supported
3	Lenient Return Policies	Time to Sale	Partially Supported	Partially Supported
3a	Return Window	Time to Sale	Insignificant	Insignificant
3b	Free Return Shipping	Time to Sale	Insignificant	Significant
3c	Restocking Fees	Time to Sale	Significant	Significant

DISCUSSION AND CONCLUSION

In this study, the value of a lenient return policy and other terms of sale in an online marketplace are examined. Data from eBay on all completed transactions involving six consumer electronics products over nine months in 2015 is used to estimate a three-stage least squares model with *Landed Price* (supply) and the *Time to Sale* (demand) as the dependent variables. The results suggest that sellers incorporate their return policies into their pricing decisions and increase the landed price of their listing when it includes a return window greater than the marketplace standard. Moreover, customers respond favorably to lenient return policies, even after controlling for price, shipping charges, product presentation, and seller characteristics.

On the supply-side, the length of the return window is found to have a strong and highly significant impact on landed price. A return window longer than the default (14 days) is associated with price premiums of approximately 2-3% over a no-returns policy. Interestingly, an insignificant difference is found between a no-return policy and the default 14-day return window with respect to the landed price, and surprisingly, return windows less than the default were found to lead to approximately 15.28% higher landed price. The magnitude of this impact is surprising; however, it suggests the value of deviations away from the institutional norm (i.e. a no-return policy or the default return window). Unfortunately, this effect is limited to only five observations, so further examination of this variable is better suited to future research.

The demand-side results suggest that customers pay attention to return policies, and the impact of return policies varies by parameter. Surprisingly, the *Default Window* and *Extended Window* options are insignificant in the *Time to Sale* equation. Meanwhile, the *Shorter Window* option is found to be negative and highly significant. Once again, while surprising, this result only applies to five observations. Future research should examine whether it is the deviation from the institutional norm that is driving this strong and significant effect.

Free Return Shipping appears to have little impact on demand as does the initial shipping charge. *Restocking Fees,* on the other hand, are found to significantly reduce demand and increase the time it takes for a product to sell. A restocking fee of any magnitude is associated with a 9.87-hour increase in the *Time to Sale*. Furthermore, the impact of restocking fees is nonlinear, with the impact differing according to the percentage and type of restocking fee. No association is found between a restocking fee of 10%; however, restocking fees of 15% and 20% are associated with approximately 14.1- and 10.84-hour increases in *Time to Sale,* respectively. Interestingly, the largest delay in *Time to Sale* is associated with restocking fees outside of the standard options (10%, 15%, 20%). *Time to Sale* was found to be prolonged by approximately 25.63 hours when one of the non-traditional restocking fees are specified.

Research Implications

Longstanding theory in operations and marketing suggests a positive relationship between lenient return policies and demand; however, empirical research has only recently begun demonstrating the true value of allowing returns, and the results have been mixed. Anderson et al. (2009) found a mail-order apparel company to earn a 20-30% price premium by allowing returns, while Shang et al. (2017b) found that eBay sellers offering the default return policy earn only a 5.2% price premium. However, despite the progress of these and other studies demonstrating the value of return allowance, the value of specific return policy components is still unclear.

Using a unique dataset, this study decomposes the return policy into several components (i.e. return window, shipping charges, free return shipping, restocking fees) and offers new insight into the value of each. The results confirm that lenient return policies impact both sellers' landed price decisions and demand; however, the impact varies by parameter. The length of the return window is shown to primarily affect *Landed Price* (supply), whereas restocking fees main impact is on *Time to Sale* (demand). Thus, a potential mismatch exists between the focus of buyers and sellers regarding return policies. Buyers' strong, negative reactions to restocking fees can counteract the benefits sellers generate with extended return windows.

Free Shipping is also shown to be positively associated with *Landed Price*. Since, only listings resulting in sales are included in the estimation, this positive association suggests that buyers are willing to accept a higher *Landed Price* to avoid losing non-

refundable shipping charges that would be lost if the product was returned. Therefore, non-refundable shipping charges serve as a form of *implicit* restocking fee that has a significant impact on *Landed Price.* No association is found between *Free Shipping* or the percentage of the landed price associated with shipping (*Percent Ship Charge*) and *Time to Sale*.

Managerial Implications

The managerial implications of this work are most applicable to sellers in online marketplaces with the freedom to customize their return policy. The results suggest that extended return windows and free shipping are effective signals of quality in online settings where information asymmetry exists. By offering a return policy more lenient than the standard policy, a seller can signal the quality of their product and their ability to handle sales and returns management. This uncertainty reduction was shown to lead to approximately 2-4% higher landed prices.

The results also suggest that sellers should be wary of using restocking fees to offset an extended return window, as restocking fees of any magnitude were found to significantly increase *Time to Sale,* by approximately 9-10 hours. Furthermore, attempts to hide restocking fees in detailed return policy descriptions appears to have the most detrimental impact on demand, causing *Time to Sale* to increase by over 24 hours.

Since, a nonrefundable shipping charge is one form of protection for sellers against losses attributed to returns, an opportunity appears to exist for sellers to increase that protection, in an implicit manner, without significantly impacting the demand for their listings. The percentage of the landed price attributed to shipping (*Percent Ship Charge*) was not found to significantly impact on *Time to Sale*. Thus, sellers could increase this percentage to build in additional monetary protection against product returns, without impacting the demand for their listings.

Chapter 3: Buy It, Try It, Rate It: The Impact of Buyer Feedback on Supply and Demand in Online Retailing

ABSTRACT

This chapter presents a theoretical and empirical analysis of the relationship between buyer feedback and supply and demand in an online marketplace. This chapter is structured as follows: Section 3.1 provides an overview of the literature on reputation systems and feedback text and formulates the research hypotheses. Section 3.2 describes the data collection and feedback classification procedures and then describes the variables used in the empirical model. The results are presented in Section 3.3, and Section 3.4 discusses the research and managerial implications as well as future research opportunities.

INTRODUCTION

A recent Forrester Research report predicts that online retail sales in the U.S. will grow by an average annual rate of 9.32% over the next five years and reach over $523 billion in 2020 (Lindner, 2016). Online marketplaces, such as Amazon Marketplace, eBay, Bonanza, Craigslist, Etsy, and eBid, have substantially lowered the barriers to entry, allowing an individual seller to open a store and begin selling products in less than 24 hours. This ease of entry has increased competition.

Internet commerce, however, suffers from substantial information asymmetry (Brynjolfsson and Smith, 2000). Due to the spatial distance between the two parties, the buyer does not have the opportunity to physically inspect products prior to purchase and is left exposed to risk from potentially incomplete or inaccurate information from the seller. The temporal distance between purchase and receipt of goods and the buyers retain/return decision may cause the buyer to devalue the product(s) and their option to return unwanted merchandise (Lee, 1998). In online marketplaces in particular, with many small to medium sized sellers, there are often very few repeat transactions. Thus, buyers must evaluate sellers' online reputations as they decide from whom to purchase.

Online feedback ratings and feedback text are important tools that provide buyers with information on sellers' online reputations (Dellarocas, 2003). Feedback can help buyers discern the trustworthiness of unknown sellers, promote trustworthy behavior, and discourage unskilled or dishonest participants from entering the market. It can also help sellers identify mistakes and improve customer service if regularly monitored.

Negative feedback can have a devastating impact on an online seller's sales and reputation, especially feedback that erodes buyers' trust in the seller (Dellarocas, 2006). Previous research has shown that a single neutral or negative feedback rating can decrease an online seller's sales growth rates by as much as 13% (Cabral and Hortacsu, 2010). While the significance of negative feedback ratings on sales is robust (Eaton, 2002; Resnick and Zeckhauser, 2002; Bajari and Hortacsu, 2003; Cabral and Hortacsu, 2010), few studies have examined the text associated with those ratings.

This study extends the literature on the value of an online reputation by quantifying and empirically testing the impact of negative feedback text on the landed price and time to sale. The following research questions are posed:

1. Does the impact of negative feedback on landed price and time to sale vary by complaint type?
2. Do successful service recoveries mitigate the negative impact of buyer complaints?
3. Does the variety of complaint types explain the non-linear impact of negative feedback?

To answer these questions, over 1.5 million feedback posts are collected from eBay, and content analysis is performed to categorize buyer comments based on transaction satisfaction, complaint type, and transaction outcome. Feedback is then aggregated to

the seller-level to create numerical measures that reflect seller skill and reputation within the marketplace. These numerical measures are then used to predict the landed price and time to sale for the sellers' listings of a common set of products over a nine-month period.

LITERATURE REVIEW AND HYPOTHESES

Background Theory

Reputation Systems

When information asymmetries exist, an effective reputation mechanism is needed to mitigate buyers' risk and incentivize sellers to provide high quality products (Zhou et al., 2008). If effective, the reputation mechanism should facilitate commerce, by decreasing buyers' uncertainty, and allow sellers to capture margins equal to their products' quality. Without it, the market may collapse (Zhou et al. 2008). See Appendix A for an overview of eBay's reputation system and the ways in which buyer, seller, and product ratings are collected.

The reputation mechanisms of many e-commerce platforms have been studied, including those of Eachnet.com (Cai et al., 2013), Taobao.com (Fan et al., 2016), and PriceMinister.com (Jolivet et al., 2016). eBay.com (eBay) has, arguably, the most commonly studied reputation mechanism: a complex feedback system that allows buyers and sellers to rate and evaluate each other following every transaction. Following each transaction on eBay, the buyer is given the option to rate the seller by

leaving a numerical rating (positive=1, neutral=0, or negative=-1) and a short comment (eBay, 2017b). Sellers can reply to buyers comments and leave the buyer a numerical (positive=1 or null=0) rating and a short comment of their own. Over time, buyers and sellers alike develop extensive feedback profiles, of text and ratings, consistent with their online reputation.

In one of the earliest studies within this domain, Resnick and Zeckhauser (2002), examined 36,233 auctions and found that over half resulted in feedback (52.1% of the time by buyers and 60.6% of the time by sellers), and it was almost always (99.1% of the time) positive. Further, they found that reputation profiles were predictive of future performance; however, the net feedback score that eBay prominently displays by each sellers' name is a weak predictor.

In a later study, Resnick and Zeckhauser (2006), used a field experiment to compare consumers' willingness-to-pay (WTP) for an established, reputable seller's product to the same seller's product under a new identity. They find that the seller can earn an 8.1% price premium by selling under his established identity, with a positive reputation, even after controlling for the shipping, billing, and payment procedures.

Several studies have provided additional evidence on the impact of eBay's reputation mechanism, and a wide range of product categories have been studied, from electric guitars (Eaton, 2002), to dolls (McDonald and Slawson, 2002) to beanie babies (Resnick and Zeckhauser, 2002). In general, eBay's count and percentage feedback

measures have consistently been found to predict final auction price (Houser and Wooders, 2000; Lucking-Reiley et al., 2007; Ba and Pavlou, 2002; Melnik and Alm, 2002; Bajari and Hortacsu, 2003; Zhou et al., 2009) and probability of sale (Bajari and Hortacsu, 2003; Eaton, 2002; Resnick and Zeckhauser, 2002). However, conflicting evidence exists on the impact of difference measures, such as the net feedback score calculated by eBay and prominently displayed next to each member's username (McDonald and Slawson, 2002; Resnick and Zeckhauser, 2002; Zhou et al., 2009).

Overall, the extant literature strongly suggests that, feedback significantly impacts buyer and seller behavior and the efficiency of this online marketplace, although the precise magnitudes vary across studies. Few studies, however, have examined the other component of eBay's reputation mechanism: the digital text attached to those ratings.

Feedback Text

Interest in the information encoded in digital text is growing (Gentzkow et al., 2017). Electronic word-of-mouth provides buyers and sellers with vital information about product quality as well as buyer and seller reputation and capabilities. A survey of customers in the consumer electronics industry conducted by KRC Research (2012) found that consumers are influenced by online reviews prior to purchase, with 65 percent of those surveyed having been inspired to buy a product that they were not considering due to a favorable review. 95% of respondents also attributed confidence in a buying decision to positive customer reviews.

Recent research has shown that the volume of review information, such as feedback comments, improve customer decision making and reduces product returns (Sahoo et al., 2018). In addition, customers have been shown to purchase additional substitutes (such as alternative colors, sizes, and products) when few reviews are available, to counteract their risk of a negative outcome (Sahoo et al., 2018). While the volume and tone of feedback has been extensively studied, there is a lack of research on the focus of buyer complaints. Furthermore, scant research exists on the comparative impact of buyer ratings and complaints.

In this study, we extend the literature on the value of an online reputation by using text analytics and content analysis to quantify a unique collection of buyer feedback from eBay and link the tone and focus of buyer comments to the demand for associated listings.

Research Hypotheses

Figure 3 depicts the paths that a feedback thread could follow and highlights the routes that can lead to a successful service recovery or to a service recovery failure. These paths are not specific to a product, buyer, or seller and apply generally across the entire range of feedback threads.

The first level of the classification tree identifies whether the feedback text contains a complaint: a comment on the seller's product or services that is negative in nature.

Nine complaint types and two complaint categories (trust-revoking and non-trust-revoking) are considered. See table 11 for a definition of each.

Trust-revoking complaints are defined as comments specifically identifying at least one flaw in the seller's product or service. As shown in table 11, trust-revoking complaints could suggest problems related to the seller's product (quality, black market), sales expertise (delivery, cancellation, misrepresentation), or post-sale practices (return/refund, communication). Miscellaneous complaints without detail on the seller's product or service as well as complaints about the price paid are considered non-trust-revoking.

The variability or range of complaint types in a seller's feedback history is captured through *Complaint Type Dispersion*. The wider the range of complaint types in a seller's feedback history, the larger the *Complaint Type Dispersion*. More information is provided on this variable in the Data and Model section.

The middle branch of the classification tree identifies whether the seller resolved the issue described by the buyer. Service recoveries may exist when the feedback indicates that an issue was resolved. If the thread includes a single complaint type that is resolved or multiple complaint types that are fully resolved, then a successful service recovery has taken place. However, if the thread includes multiple complaint types with one or more issues left unresolved, then the service recovery attempt is considered a failure.

The final branch of the feedback classification tree represents the end satisfaction of the buyer as described within their feedback comments. In this study, satisfaction is observed from the buyer perspective and is either positive, neutral, or negative, depending on the tone, content, and focus of the buyer feedback. Clearly, if the buyer does not make a complaint, then the feedback cannot be negative. Threads without complaints are almost always positive but can be neutral if the buyer's comments lack positive and negative sentiment. These are typically very brief feedback comments, such as "Product received" or "Fine."

In the online reputation literature, neutral and negative ratings are commonly paired together (Cabral and Hortacsu, 2010; Resnick and Zeckhauser, 2002; Subramanian and Subramanyam, 2012Shang et al., 2017b). However, here, they are broken out into separate categories to distinguish between successful and unsuccessful service recoveries. A service recovery is deemed successful if the buyer's comments include at least one complaint and the overall transaction satisfaction of the buyer is positive or neutral. A service recovery is considered unsuccessful if at least one complaint exists in the buyer feedback and the transaction satisfaction is negative. Based on our definition of complaint resolution, resolved complaints cannot be negative. Conversely, a complaint cannot be considered unresolved and the transaction outcome neutral or positive.

Table 12 lists the seven potential transaction outcomes. The traditional or expected outcome is that the seller delivers the product and the buyer retains it. Absent fraud, this is the outcome that the buyer and seller anticipated when completing the sale. Several other, unexpected outcomes could also result. The buyer may not retain the product and instead return or exchange the item(s) or the buyer may keep the item and request a partial or full refund. The buyer could also never receive the item due to a seller/buyer cancellation or delivery failure. Each of these six unexpected outcomes was recorded during the tagging process (see Ap. C.); however, they were later aggregated into two categories (Returned and Nonreceipt) to increase the tractability of the analysis.

Each path in the feedback classification tree could result in any of the seven transaction outcomes. However, certain outcomes are expected to be more prevalent along certain paths. Product retention is expected to be positively associated with positive satisfaction, whereas nonreceipt is expected to be positively associated with negative satisfaction. The return outcome is expected to be split amongst the three satisfaction categories and a function of sellers' service recovery abilities.

Figure 3: Feedback Classification Tree

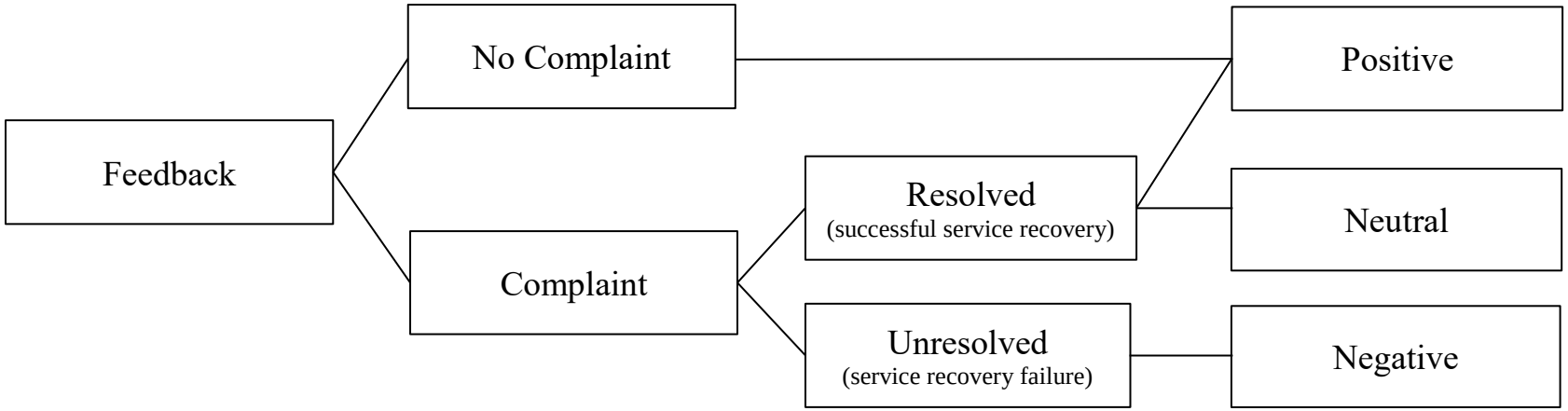


Table 11: Complaint Type Categories and Definitions

Complaint Type	Definition
Non-trust-revoking	Complaints that do not specifically state a problem with the seller's product or service or are unjustified.
Nonspecific	Buyer indicates the existence of a problem during the transaction but does not provide further detail.
Price	Buyer complains about the price they agreed to pay for the product(s) and/or shipping.
Trust-revoking	Complaints about a specific aspect of the seller's product or service, other than price.
Quality	Buyer complains that the product(s) is of low quality, broken, defective, or missing an item or part.
Delivery	Buyer complains that the product(s) arrived late or not at all, had poor packaging, or was the incorrect item.
Cancellation	Buyer complains that the seller reneged on the transaction.
Misrepresentation	Buyer complains that the seller was deceptive in their product(s) description.
Return/refund	Buyer complains about the seller's process for handling returns or issuing refunds.
Black market	Buyer complains that the transaction involved some aspect of illegality.
Communication	Buyer complains that the seller was unresponsive, unprofessional, ineffective, or slow to respond to questions or concerns.

Table 12: Transaction Outcome Categories and Definitions

Transaction Outcome	**Definition**
(I) Expected	The expected outcome.
(A, 1) Retained	Buyer kept the product.
(II) Unexpected	An unexpected outcome.
(B) Return	Aggregate measure of return, exchange, or refund outcome.
(2) Exchange	Buyer exchanged the product.
(3) Refund	Buyer kept the product and received a full or partial refund.
(4) Return	Buyer returned the product.
(C) Nonreceipt	Aggregate measure of non-delivery or cancellation.
(5) Non-delivery	Buyer never received the product, although seller claims product were shipped.
(6) Buyer cancellation	Buyer cancelled the transaction prior to the product being shipped.
(7) Seller cancellation	Seller cancelled the transaction prior to shipping the product.

Service Recoveries

The first component of buyer feedback that I examine is the transaction satisfaction of the buyer. In contrast to most of the previous online reputation literature, transaction satisfaction is measured by human interpretation of feedback text, instead of the numerical rating provided by the buyer.

While beneficial to new sellers, positive feedback is largely taken for granted by established online sellers, and not surprisingly, previous research has shown that positive feedback ratings have little effect on sellers' sales growth once a positive online reputation has been established (Livingston, 2002). Thus, transaction satisfaction should be positively associated with sellers' sales growth rates, but at a diminishing marginal rate.

On the other hand, previous literature has shown that negative feedback ratings can significantly alter established and unestablished reputations alike (Eaton, 2002; Resnick and Zeckhauser, 2002; Bjari and Hortacsu, 2003). In situations where a seller does not resolve an issue that arose during a transaction, and the buyer publicly discloses this fact via feedback text, the seller's sales growth and the demand for their current listings should decrease. Therefore, negative feedback text should be negatively associated with demand in a linear fashion.

One benefit of measuring transaction satisfaction through feedback text is that it accounts for the possibility of a buyer changing her opinion after she has posted her

numerical rating. In such a case, the buyer may praise the seller in follow-up comments and reveal positive satisfaction with the transaction, despite a negative rating. As procedural justice theory predicts, successful service recovery attempts may increase positive word-of-mouth, repurchase intentions, (Maxham, 2001; Maxham and Netemeyer, 2002; Maxham and Netemeyer, 2003), and customer loyalty (Homburg, and Fürst, 2005; Griffis et al. 2012).

Thus, by responding to the complaint in such a manner that changes the customer's transaction satisfaction from negative to neutral or positive, the seller can promote trust with future customers (Doney and Cannon, 1997; Ba et al., 2003). Therefore, feedback posts that reveal positive or neutral satisfaction despite a complaint from the buyer (*Service Recoveries*) are expected to increase demand. Evidence of successful service recoveries will therefore, increase the landed price of future listings and decrease the time it takes for those listings to close. More formally:

Hypothesis 1a: *Service recoveries and landed price are positively associated.*

Hypothesis 1b: *Service recoveries and time to sale are inversely associated.*

Trust-Revoking Complaints

One of the largest contributions that this study makes to the online reputation literature is the analysis of complaint type on demand. The impact of negative feedback ratings in isolation is well established; however, the other component, feedback text, has largely been overlooked, due to the difficulty in creating accurate quantitative

measures from the text. Here, the text attached to feedback ratings is examined using content analysis and the impact of various complaints types is examined.

Feedback complaints come in many forms. Some are trivial, while others reveal substantial problems in sellers' sales, delivery, and returns management practices. Negative feedback that is non-specific or unjustified (e.g. complaints about the agreed price) are likely to have little impact on future demand. However, complaints about specific problems related to the seller or its products can significantly alter buyers' trust. For example, trust in buyer-seller relationships has been shown to be a function of seller size, reputation, expertise, and power (Doney and Cannon, 1997). Specific complaints, such as those indicating product misrepresentation, poor returns management practices, or the sale of illegal items, may diminish buyers' perceptions of seller reputation and expertise, and therefore, revoke trust in the seller.

Justice theory states that customers evaluate firms based on transaction outcomes, the procedures used to reach those outcomes, and the nature of interpersonal treatment throughout the process (Tax et al., 1998). Thus, specific complaints about product quality, product authenticity, product descriptions, delivery issues, return policies, cancellations, and communication failures should all significantly impact customers' evaluations of the firm; however, non-specific complaints or complaints about the agreed price are likely to have little impact.

For example, a lenient return policy is one way for a seller to signal quality (Moorthy and Srinivasan, 1995). However, if negative feedback exists related to the seller's process for handling returns, then the quality of that signal will quickly diminish. Furthermore, exceptional claims of quality have been shown to result in substantial price premiums for rare goods (31%-51% in the case of Jin and Kato, 2006); however, such claims are likely to be deemed infeasible if evidence of product misrepresentation exists in the sellers' feedback history. Similarly, black market complaints will discourage purchase due to the inherent illegality implied. From this logic, we predict the following:

Hypothesis 2a: *Trust-revoking complaints and landed price are inversely associated.*

Hypothesis 2b: *Trust-revoking complaints and time to sale are positively associated.*

Complaint Type Dispersion

In some situations, negative feedback may also have compounding effects. For example, Cabral and Hortacsu (2010) found that additional negative feedback ratings arrive 25% more frequently after a seller receives its initial negative rating. The authors found that these additional negative ratings have far less of an impact on the sellers' sales growth, however they did not consider the text associated with those ratings.

Based on the critical assumption that customers read the text associated with negative ratings, additional negative feedback could provide buyers with new information about the quality and reputation of the seller and, therefore, have

differential effects. For example, if the new feedback reveals previously unknown problems with the sellers' sales and return management processes, then the diminished marginal effect may not occur. On the other hand, if the additional feedback simply confirms an already identified issue in the seller's management practices, then it may have a weaker effect than the initial post. Thus, the dispersion or the range of complaint types evident in sellers' feedback profiles will negatively impact listing demand. The following are hypothesized:

Hypothesis 3a: *After controlling for the number of positive, negative, and neutral threads, complaint type dispersion and landed price are inversely associated.*

Hypothesis 3b: *After controlling for the number of positive, negative, and neutral threads, complaint type dispersion and time to sale are positively associated.*

DATA AND MODEL

The following subsections outline the data collection, cleaning, and feedback classification procedures. For a more detailed description of each topic, refer to Appendix B.

Data Collection and Cleaning

Using a structured web-crawling procedure, data on all completed transactions involving six consumer electronic products on eBay was gathered over the course of seven months (May-November 2015). Since eBay stores the results of listings ending

in a sale for 90 days and the results of unsold listings for 30 days, the script compiled every completed transaction involving the six products from February 14, 2015 to November 19, 2015 (i.e. the final script execution date). More specifically, detailed information was collected on the transaction, product, and seller involved in fixed price (buy-it-now) listings of new GoPro Hero4 (black, silver, and session edition) cameras, Microsoft Xbox One entertainment systems (with and without the Kinect sensor), and Bose QC25 headphones. The compiled data was split into two samples: completed listings (sales) and seller feedback profiles (feedback).

The sales data includes every completed transaction involving the six products over the nine months observed. Both sales and unsold listings are recorded. The price paid for the product, the quantity purchased, and the eBay IDs of the buyer (partially abbreviated) and seller (unabbreviated) are recorded. The data includes complete information on each listing, including the item condition, item location, item ID, product category, listing format, time to sale, number of images provided, length of the item description, presence of seller badges, and listing titles. Other terms of sale, including the return policy and the shipping service and cost are also recorded.

The feedback data includes the entire feedback history of every seller up to the final web crawling execution date (November 19, 2015). This includes a complete breakdown of the publicly available information on each seller, such as the sellers' tenure on eBay (i.e. how long the username has existed), net feedback score, and number of overall feedback ratings that are positive, neutral, or negative over the last

month, six months, and year. The detailed ratings on the sellers' item description, shipping and handling, shipping speed, and communication over the last year are recorded as well as the entire set of buyer feedback comments from the creation of each seller ID until November 19, 2015.

Each seller sells at least one of the six consumer electronic products in the sales data, and could sell, and receive feedback on, many other products as well. The feedback data is organized into "threads," which include the initial feedback from the buyer as well as any of their follow-up comments or replies from the seller.

The web-crawling script recorded 1,435,142 feedback posts across all seller profiles. 3,521 threads with missing information and 11,858 threads in foreign languages were removed. Since the same set of sellers are attached to multiple listings, there are several repeated observations and only 568,109 of the feedback threads are distinct. These were the threads used for feedback classification and the creation of the seller reputation measures. More information on those procedures is provided in the next section.

Feedback Classification and Seller Reputation Measures

Current Reputation Measures

The eBay feedback system allows members to rate each other and provide feedback after each transaction. Buyer feedback consists of a satisfaction rating (positive, neutral, negative) and a short comment. Seller feedback is restricted to either positive

or neutral ratings, to reduce retaliatory ratings from buyers, and a short comment. Over time, these ratings and comments accumulate and produce a reputation profile for each user (as both a buyer and seller).

An overall feedback score is generated for each user, with positive ratings contributing one point, neutral ratings having no impact, and negative ratings reducing scores by one. (Negative feedback scores are possible.) This reputation score is displayed in parentheses next to the user ID wherever her ID appears. Star levels, representing feedback milestones, are also presented next to users' feedback scores to identify their experience on the marketplace. The first star level (yellow) is given after 10 feedback points have been earned and the final star level (red shooting star) is awarded after 100,000 feedback points. This reputation system, also known as the Feedback Forum, is vital to the success of eBay (Resnick et al., 2000).

The impact of numerical feedback ratings has been extensively studied, while less attention has been paid to the short comments left by buyers and sellers on online marketplaces. This study fills this gap in the literature as one of the first to quantify the feedback text provided by buyers and the responses sellers into outcome measures that reflect the overall tone of the feedback "threads" and reflect sellers' skill and reputation within the marketplace.

Alternative Reputation Measures

To compare the impact of feedback text to numerical ratings and to distinguish

amongst the complaints within the feedback, a text classification process is required. Several methodologies have been developed to study "text as data." See Gentzkow et al (2017) for a methodological critique of prior work in this area. Below a brief overview of the classification methodology used in this study is presented. For a complete description of the process and the category-specific word dictionaries used to segregate each feedback thread, see Appendix C.

To quantify the free-form text of the feedback threads, a content-based approach is used in this study. More specifically, the traditional text-classification approach proposed by Salton (1971, 1989) known as the vector-space model or "bag of words" approach is used along with necessary adjustments to match the research setting. The content analysis produces a set (dictionary) of terms associated with each transaction outcome, satisfaction level, and complaint type. From these keywords, a set of seller-related variables is established by searching the sellers' feedback profiles for the terms in each category-specific dictionary and summing the pre-assigned weights (prevalence scores) associated with each matched term.

The vector-space model begins with the elimination of punctuation, casing, extremely high- and low-frequency terms, synonyms, non-content-bearing words, variations based on prefixes and suffixes, structural phrases, and common spelling errors (Spangler and Kreulen, 2007; Gentzkow et al. 2017). Then, clustering techniques (e.g. Correlation Coefficient K-means Clustering) and feature ranking methods (e.g. Robertson's selection value, correlation coefficients) are used to identify the features

(terms and phrases) that are highly prevalent in outcome categories beyond what would be expected based on term-frequency alone (Fan et al., 2005). These category-specific dictionaries or "taxonomies" are created automatically via software and then refined via domain knowledge and iterative analysis (Spangler and Kreulen, 2007).

Each dictionary contains a list of words and associated weights (prevalence scores) that reflect the prediction quality of the term. These dictionaries are then used to automate the feedback classification process for the remaining threads in the sample. An algorithm identifies the terms from the category-specific dictionaries in each thread and then sums the prevalence scores, resulting in numerical scores for the likelihood associated with each category. The predicted outcomes are based on the highest score within each tagging category (outcome, satisfaction, complaint type), and only a single outcome is assigned per category (i.e. multiple complaint types are not permitted).

In the final step of the feedback classification process, the category-specific dictionaries are used to score the remaining feedback posts in the holdout set. The same pre-processing steps described previously are performed on each feedback thread, and then, each post is assigned an overall prevalence score for each category, based on the sum of the prevalence (CC) scores for each matching word from the category-specific word dictionary. The highest sum in each category is designated as the outcome. If none of the outcomes within a category (e.g. positive, neutral, negative) is predicted, then the most conservative value (i.e. positive satisfaction, expected outcome, and no

complaint) is assumed. Three scoring units were considered: unigrams (words), bigrams (two-word phrases), and trigrams (three-word phrases).

Table 13 summarizes the predicted values of each of the three scoring units. As expected, the unigram results identified the most complaints (*Threads with Complaint*=10.61%), the highest percentage of *Unexpected Outcomes* (10.52%) and the highest percentage of *Negative Threads* (11.36%). The trigram results produced the fewest number of complaints (*Threads with Complaint* 4.89%), the lowest percentage of *Unexpected Outcomes* (1.68%), and the lowest percentage of *Negative Threads* (3.16%). The bigram results were moderate, and the values typically fell in between those of the other two scoring units. The structure of the results is as expected, since the trigram scoring unit searches for specific three-word-phrases, whereas the unigram and bigram scoring units search for single words and two-word-phrases, respectively. Since, the most conservative values for each category were assumed when the predicted outcome was unclear, the more selective criteria of the trigram scoring unit led to fewer alternative values. The same is true to a lesser extend for the bigram scoring unit compared to the unigram scoring unit.

Delivery was the most common complaint in the unigram and bigram results, while *Misrepresentation* was the most common in the trigram results (*Delivery* was second). *Quality, Delivery, and Misrepresentation* were the top three complaint types for all three scoring units. *Black Market, Cancellation, and Return/Refund* complaints were less common and ranked between 5-7 across the three methods. *Communication*

complaints were moderately common and ranked 4th using all three scoring units. Service recoveries were fairly common, ranging between 14.93% and 35.52% of all threads with at least one complaint. Transaction outcomes are also listed in table 13, although they are not directly used in the regression analysis. The expected outcome was found in most cases. Finally, consistent with several studies that analyze eBay's numerical rating system (Ba and Pavlou, 2002; Resnick and Zeckhauser, 2002; Lucking-Reiley et al., 2007; Zhou et al., 2009; Shang et al., 2017) most threads were classified as having positive sentiment. The unigram, bigram, and trigram scoring units classified 88.43%, 91.55%, and 95.57% of the threads as positive, respectively.

Using a sample of 36,233 sold items, Resnick and Zeckhauser (2002) found that 0.6% of buyer ratings were negative, 0.3% were neutral, and 99.1% were positive. Similarly, Shang et al. (2017) found that 99.76% of seller ratings were positive and only 0.24% of ratings were neutral or negative across 3,139 sold items. While the sentiment measures produced through the feedback classification process (*Positive Threads, Neutral Threads, Negative Threads*) can pick up additional complaints and nuisances not reflected in numerical (-1,0,1) ratings, I elected to follow the most conservative approach that best matched the sentiment reflected in numerical ratings. Thus, based on the predicted outcomes and expectations generated from previous studies, the trigram scoring unit was deemed most appropriate and selected for the empirical analysis. The empirical models were also estimated using the other scoring methods and the results are available upon request. The improvement of the feedback

classification process, through combination and optimization of the scoring methods and identifiers, is an interesting avenue for future research.

Table 13: Predicted Outcomes by Scoring Unit

	Unigrams		Bigrams		Trigrams	
Field	**Freq.**	**Percent.**	**Freq.**	**Percent.**	**Freq.**	**Percent.**
Complaints						
Complaint-Free Threads	507,813	89.39%	511,838	90.10%	540,328	95.11%
Threads with Complaint	60,296	10.61%	56,271	9.90%	27,781	4.89%
Complaint Types						
Non-Trust Revoking Complaints	799	0.14%	5,644	0.99%	3,229	0.57%
Nonspecific	517	0.09%	3,639	0.64%	2,578	0.45%
Price	282	0.05%	2,005	0.35%	651	0.11%
Trust-Revoking Complaints	59,497	10.47%	50,627	8.91%	24,552	4.32%
Quality	14,630	2.58%	11,647	2.05%	3,668	0.65%
Delivery	27,189	4.79%	15,540	2.74%	4,760	0.84%
Cancellation	928	0.16%	1,738	0.31%	925	0.16%
Misrepresentation	8,790	1.55%	13,945	2.45%	11,166	1.97%
Return/Refund	334	0.06%	2,395	0.42%	1,209	0.21%
Black Market	1,166	0.21%	553	0.10%	396	0.07%
Communication	6,460	1.14%	4,809	0.85%	2,428	0.43%
Service Recovery						
Service Recoveries	9,003	14.93%	18,033	32.05%	9,869	35.52%
Service Recovery Failures	51,293	85.07%	38,238	67.95%	17,912	64.48%
Transaction Outcome						
Expected Outcomes (Retained)	508,338	89.48%	534,227	94.04%	558,568	98.32%
Unexpected Outcomes	59,771	10.52%	33,882	5.96%	9,541	1.68%
Nonreceipt	47,519	8.36%	18,830	3.31%	3,680	0.65%
Returned	12,252	2.16%	15,052	2.65%	5,861	1.03%
Transaction Satisfaction						
Positive Threads	502,386	88.43%	520,110	91.55%	542,954	95.57%
Neutral Threads	1,164	0.20%	9,065	1.60%	7,191	1.27%
Negative Threads	64,559	11.36%	38,934	6.85%	17,964	3.16%

Note 1: The dataset includes 568,109 distinct threads
Note 2: Service Recovery percentages are based on the threads with a complaint

Finally, the trigram outcome measures were aggregated to the seller-level to represent the written feedback history of the observed sellers. For sellers with multiple listings, the listing completion date and time are used to identify the feedback history available at the time of sale.

Dependent Variables

To measure the overall impact of feedback text on demand a two-equation system is estimated. First, the *Landed Price* is regressed on the characteristics of the seller, measures of its feedback history, and the listing characteristics. Then, the fitted value of *Landed Price,* seller characteristics, feedback history, and listing characteristics are used to predict the *Time to Sale*. The second-stage equation estimates the hours between the listing creation and listing close and reflects the market demand for the listing. After controlling for the product and presentation of the listing, the longer the *Hours to Sale*, the lower the demand for the listing.

The *Landed Price* reflects the final delivered price of the item(s) included in the listing. This value, which includes the price to purchase the product(s) as well as any shipping charges, was determined by the seller and deemed acceptable by the buyer (i.e. only listings that resulted in a sale are included in the analysis). The average *Landed Price* is 356.46, with a minimum of 223.04 and a maximum of 495.95.

Time to Sale is the minutes, hours, and days from the listing creation to the listing close. Since only listings that resulted in a sale are considered, this variable measures the time that it takes for the products in a listing to sell. The time of the listing creation and the listing close are measured to the minute and therefore, time to sale is captured in both minutes (*Minutes to Sale*), hours (*Hours to Sale*), and days (*Days to Sale*). Since the *Time to Sale* is generally brief, with a mean of 47.47 hours, the *Hours to Sale* measure is used in the regression analysis.

Independent Variables

To test the hypotheses presented earlier, the feedback text in the sample is first categorized using text analytics, and then seller-level measures of transaction satisfaction, transaction outcome, and complaint type are developed to test the research hypotheses. As described in the following subsections, several variables related to service recovery, presence and focus of complaints, transaction outcome, and satisfaction of the buyer are created.

Service Recoveries

To test Hypothesis 1, *Service Recoveries* is created to measure the number of successful service recoveries within each seller's feedback profile. A service recovery is deemed successful if the satisfaction of the buyer is positive or neutral, despite at least one complaint in the buyer feedback. For example,

> *"Feedback from the buyer: Sold item as BNIB but was USED. Has dirt, multiple scratches, missing box contents. ----- Follow-up by the buyer: Was mistake, made offer to avoid hassle or refund, quick response, happy outcome."*

In most cases, a successful service recovery involves either a reply by the seller or a follow-up comment from the buyer that indicates the seller resolved at least one of the issues that the buyer faced. For more information on how this variable is measured, please see the Data Coding section in Ap. C.

Trust Revoking Complaints

By examining the text associated with feedback ratings, the complaint type can be identified. As hypothesized previously, trust-revoking complaints are expected to negatively impact demand, while other types of complaints are expected to have an insignificant impact (Hypothesis 2). To test this hypothesis, a measure of the percentage of each seller's total complaints that are trust-revoking (*Trust Revoking Complaints*) is created. In this study, all complaints are considered trust-revoking, except complaints about price and complaints that are nonspecific (*Non-Trust-Revoking Complaints*), such as the following:

> *Feedback from the buyer: I could have found these at Lowes for $2.50 a whole box. ----- Reply by the seller: Yes. U might of. Negative feedback not valid for the product or my service. Sorry.*

> *Feedback from the buyer: Would not do business again ----- Reply by the seller: What was the issue? I never got any message from you saying anything was wrong.*

Complaint Type Dispersion

Complaints that identify new problems in a seller's sales or returns management practices are expected to have a greater impact on demand than complaints that reiterate previously known flaws (Hypothesis 3). That is, the more varied the complaint type category in the seller's feedback profile, the stronger the negative impact on her future sales will be. Thus, disaggregate measures are necessary to distinguish between the specific complaint types. Therefore, seven variables were included to capture the percentage of feedback posts indicating each type of complaint (see Appendix D for a complete description of each). These values were then aggregated to the seller-level to form a measure of dispersion amongst the complaint type categories for each seller. *Complaint Type Dispersion* is defined as the number of specific complaint types (1-7) that appear in each seller's feedback history. If a seller's feedback history has at least one thread with a complaint of each type, then their *Complaint Type Dispersion* equals seven. If a seller's feedback does not include any trust-revoking complaints, then their *Complaint Type Dispersion* is zero. Multiple threads of the same complaint type do not impact the *Complaint Type Dispersion* measure. Other measures of *Complaint Type Dispersion*, including the variance of complaint types per seller and the ratio of the variance-to-mean, are reserved for future research.

Descriptive Statistics

Table 14 summarizes the seller-level measures of reputation. As expected, most sellers had primarily positive feedback. An average seller was found to have approximately 127 *Positive Threads*, 2 *Neutral Threads*, and 4 *Negative Threads.* On average, a seller had approximately 6 threads with *Trust-Revoking Complaints,* 1 thread with *Non-Trust-Revoking Complaints,* and 127 threads with *No Complaints.* Sellers

had on average 2.32 *Service Recoveries* and an average *Complaint Type Dispersion* of 2.5. The maximum *Complaint Type Dispersion* was 7, meaning that at least one seller's feedback profile included all seven complaint types.

Table 14: Seller-Level Reputation Measures

Variable	Mean	Std. Dev.	Min.	Max.
Positive Threads	127.33	137.06	0	777
Neutral Threads	1.68	2.3	0	17
Negative Threads	3.93	4.69	0	30
Service Recoveries	2.32	2.91	0	18
No Complaint	126.7	136.58	0	773
Trust-Revoking Complaints	5.65	6.47	0	41
Non-Trust-Revoking Complaints	0.76	1.2	0	7
Complaint Type Dispersion	2.51	1.85	0	7

Controls

Based on the analytical consumer returns literature and empirical research using eBay data, several control variables are included in the regression model (Rabby and Shahriar, 2016; Rao et al., 2017; Subramanian and Subramanyam, 2012; Shang et al., 2017b). These variables account for differences in product presentation, listing characteristics, and seller reputation. Additional factors related to the salvage value of the product and seller ability are also included to account for endogeneity related to omitted variable bias.

Seller Characteristics

- The average transaction satisfaction of the buyer is measured through the feedback classification process previously described. Four measures are produced. *Positive*

Threads measures the number of feedback posts in a seller's feedback history that indicates positive buyer satisfaction, *Neutral Threads* is a count of the posts indicating neutral satisfaction, and *Negative Threads* is a count of the posts indicating negative buyer satisfaction. *Neutral-Negative Threads* is the combination of *Neutral Threads* and *Negative Threads*.

- Sellers with more experience in the eBay marketplace may have earned some brand loyalty, developed a better understanding of the competition, and gained skills tailored to the marketplace, which could impact the demand for their listings. Thus, *Seller Tenure* is controlled for with a variable that measures the days from the creation of the seller ID on the eBay marketplace to the date of sale (i.e. listing completion).

Listing Characteristics

The following variables are included to control for the characteristics of the listing:

- Return policies are represented with four variables: *Window 14, Extended Window, Restocking Fee, and Free Return Shipping. Window 14* is a dummy variable for a 14-day return window and *Extended Window* is a dummy for a return window greater than 14 days. *Restocking Fee* takes a value of one if any restocking fee is charged on returned items, and *Free Return Shipping* equals one if the seller agrees to pay for return shipping charges.
- Three variables account for upgrades in the shipping service. The default shipping service (economy) serves as the base and *Standard Shipping, Expedited Shipping,*

and *Overnight Shipping* are used to represent 1-5-day, 1-3-day, and 1-day services, respectively.

- *Images* is a count of the product images on the listing page, and *Description Length* is the total number of characters (including spaces) used to describe the product. Both characteristics are a function of the latent ability of the seller and commonly included in studies using eBay data (Lei, 2011; Melnik and Alm, 2002; Shang et al., 2017).
- *Previously Sold* equals one if the quantity of previously sold units is displayed on the listing page and zero otherwise.
- *Weeks from Launch* measures the number of weeks from the product's release to the date of sale. This variable reflects the decrease in demand over the product's lifecycle and accounts for the deterioration of the product's salvage value.
- *Preorder* controls for 82 sales that took place prior to product launch.
- *One TB HDD* accounts for the upgraded hard drive included in some Xbox special editions, and *Kinect* controls for the inclusion of the Kinect sensor in Xbox listings.
- Finally, twenty product-specific dummies are included to control for unobserved differences in demand across products. Note that these variables account for differences in the six base products as well as special edition models.

Regression Model Specification

To test the hypotheses presented earlier, the following system of equations is estimated.

Landed Price=f(NonComplaints, Trust-Revoking Complaints, Non-Trust Revoking Complaints, Service Recoveries, Complaint Type Variance, Seller Characteristics, Listing Characteristics)

Time to Sale=f(LandedPrice(fitted), NonComplaints, Trust-Revoking Complaints, Non-Trust Revoking Complaints, Service Recoveries, Complaint Type Variance, Seller Characteristics, Listing Characteristics)

The first equation estimates the impact of buyer feedback, seller characteristics, and listing options on the landed price selected by the seller. The second equation includes a fitted value of the landed price as well as the listing options, seller characteristics, and measures of seller quality and reputation evidenced in buyer feedback.

The sign and significance of *Service Recoveries*, *Trust-Revoking Complaints*, and *Complaint Type Variance* are used to test Hypothesis 1, 2, and 3, respectfully. Seller- and listing-related controls are included in both equations.

ESTIMATION AND RESULTS

Landed Price Regression Results

Table 15 presents the regression results for the first equation with *Landed Price* as the dependent variable. Five models are presented with different combinations of measures representing the research hypotheses. Models 1 and 2 are used to test hypothesis 1a, Model 3 is used to evaluate Hypothesis 2a, and Models 4 and 5 are used to test Hypothesis 3a. In Models 1 and 4, neutral and negative threads are combined into a single measure (*Neutral-Negative*), as is commonly done in the literature with numerical feedback ratings (Cabral and Hortacsu, 2010; Resnick and Zeckhauser, 2002; Subramanian and Subramanyam, 2012; Shang et al., 2017b). In Models 2 and 5,

Neutral Threads and *Negative Threads* are included as separate predictors to test the robustness of the results without the neutral-negative combination assumption, which has been challenged in recent research (Rabby and Shahriar, 2016).

Each model includes the full set of seller, listing, and product controls. The results related to the return policy controls are included in the table and are consistent with the previous literature and those of Essay 1. A return window greater than the default (14+ days) is estimated to be worth approximately a 2-3% increase in the *Landed Price*, while the default return window of 14 days has an insignificant impact on *Landed Price*. *Free Return Shipping* was also found to have an insignificant impact on *Landed Price*, and surprisingly, *Restocking Fees* were found to have significant and positive impact on *Landed Price*. Once again, *Restocking Fees* were found to have a detrimental impact on *Time to Sale*, and in contrast to Essay 1, both the default return window (*Window 14*) and an *Extended Window* were found to reduce the *Time to Sale*.

As expected, the combined count of neutral and negative threads (*Neutral-Negative Threads*) was associated with reductions in *Landed Price* and increases in *Time to Sale*. Positive and neutral threads, however, were found to have an insignificant impact on *Landed Price*, however, they were shown to strongly impact time to sale.

The adjusted R^2 values are also high in each model, suggesting that a substantial portion of the variance in *Landed Price* and *Time to Sale* are explained by these regressors.

Models 1 and 2 are used to test the hypothesis that *Service Recoveries* are positively associated with *Landed Price* (H1a). In both models, the coefficient on *Service Recoveries* is positive and significant at the 1% level, which supports **Hypothesis 1a**. Since *Service Recoveries* is a count measure and the *Landed Price* is in log form, the coefficient of 0.0023 indicates that each additional *Service Recovery* results in a .23% increase in the *Landed Price*. With an average *Landed Price* of $356.25, the additional service recovery equates to approximately $0.82 per listing. Since, the buyer feedback, and hence the *Service Recovery,* is visible on all the seller's listings, the .23% increase in *Landed Price* could impact all the seller's listings. Assuming an average of 100 sales per month, the *Service Recovery* is worth approximately $82 per month.

Model 1 includes two measures of transaction satisfaction: *Positive Threads* and *Neutral-Negative Threads*. The coefficient for *Neutral-Negative Threads* is negative and statistically significant, as expected, while the coefficient for *Positive Threads* is insignificant. Model 2 disaggregates the neutral and negative threads and reveals that *Negative Threads* significantly impact *Landed Price*, whereas *Neutral Threads* are insignificant. Thus, these two satisfaction levels differ with respect to their impact on demand, which supports the recent results of Rabby and Shahriar, 2016.

The third model is estimated to compare the impact of *Trust-Revoking Complaints* to the impact of *Non-Trust-Revoking Complaints*. Trust-Revoking Complaints, which specifically identify a flaw in a seller's product or service, are expected to be inversely

associated with *Landed Pri*ce, whereas *Non-Trust-Revoking Complaints* that are unspecific or unjustified comments on the agreed price are expected to have an insignificant impact (H2). The results support **Hypothesis 2a**, suggesting the two complaint categories have distinct impacts on *Landed Price*. The coefficients for *Non-Trust-Revoking Complaints* and *Complaint-Free Threads* are both very close to zero and insignificant. This result suggests that the text associated with numerical ratings plays an important role in determining the overall impact on the *Landed Price*.

The *Service Recoveries* variable also remains highly significant after the inclusion of the *Trust-Revoking Complaints* and *Non-Trust-Revoking Complaints* measures, and the magnitude of the coefficient increases to 0.0031, offering additional support for Hypothesis 1a.

Models 4 and 5 are used to test the impact of *Complaint Type Dispersion* on *Landed Price* (H3a). *Complaint Type Dispersion* measures how many of the seven specific complaint types appear in each seller's feedback history. **Hypothesis 3a** predicts that after controlling for the number of positive, negative, and neutral threads the wider the range of issues documented in the feedback profile, the lower the *Landed Price*. The coefficient on *Complaint Type Dispersion* is -0.0017 and significant at the 5% level in both models. Thus, the results support Hypothesis 3a.

Once again, the disaggregate neutral and negative satisfaction measures appear to be more appropriate, with *Negative Threads* accounting for nearly all the statistical

strength of the aggregate measure. The *Service Recoveries* variable is also highly significant and consistent with the earlier results.

Table 15: First-Equation Regression Results

DV = Log Landed Price	Model 1 β (t)	Model 2 β (t)	Model 3 β (t)	Model 4 β (t)	Model 5 β (t)
Constant	5.5686*** (759.660)	5.5689*** (758.560)	5.5701*** (756.26)	5.5699*** (758.10)	5.5700*** (757.38)
Window 14	-0.0021 (-1.14)	-0.0022 (-1.17)	-0.0021 (-1.10)	-0.0017 (-0.89)	-0.0017 (-0.90)
Extended Window	0.0221*** (4.39)	0.0219*** (4.35)	0.0220*** (4.33)	0.0217*** (4.32)	0.0217*** (4.30)
Free Return Shipping	0.0077 (0.68)	0.0079 (0.69)	0.0086 (0.75)	0.0080 (0.71)	0.0081 (0.71)
Restocking Fee	0.0123*** (4.260)	0.0125*** (4.310)	0.0126*** (4.36)	0.0119*** (4.13)	0.0120*** (4.13)
Positive Threads	0.0000 (1.09)	0.0000 (1.08)		0.0000 (1.07)	0.0000 (1.07)
Neutral-Negative Threads	-0.0013*** (-4.02)			-0.0011*** (-3.12)	
Neutral Threads		-0.0009 (-1.24)			-0.0009 (-1.24)
Negative Threads		-0.0014*** (-3.94)			-0.0011*** (-2.93)
Service Recoveries	0.0023*** (4.43)	0.0021*** (3.64)	0.0031*** (4.62)	0.0026*** (4.79)	0.0025*** (4.09)
Complaint-Free Threads			0.0000 (0.92)		
Trust-Revoking Complaints			-0.0016*** (-4.35)		
Non-Trust-Revoking Complaints			0.0001 (0.14)		
Complaint Type Dispersion				-0.0017** (-2.36)	-0.0017** (-2.29)
Transaction Controls	Included	Included	Included	Included	Included
Product Controls	Included	Included	Included	Included	Included
R^2:	0.8640	0.8640	0.8641	0.8641	0.8641
Observations:	6519	6519	6519	6519	6519

* p<0.10, ** p<0.05, *** p<0.01

Time to Sale Regression Results

The regression results for the second-stage equation are presented in table 16. In all five models, the dependent variable is the time to sale measured in hours (*Hours to Sale*). Models 1 and 2 are used to test Hypothesis 1b, model 3 tests Hypothesis 2b, and models 4 and 5 represents Hypothesis 3b. Seller, listing, and product controls are included in all models.

The R^2 values range from 0.9293 to 0.9295, indicating that a very high proportion of the variance in *Hours to Sale* is explained with these predictors. The coefficient on the fitted value of *Landed Price* is positive, highly significant ($p<0.01$), and stable across the five models. The *Landed Price* coefficient in Model 5 is 1.0359 indicating that a $1 increase in the Landed Price is associated with an approximately 1.04 hour increase in the time to sale.

The results related to the return policy are consistent across the five models, confirm the results from the first essay, and make intuitive sense. On average, a listing with a 14-day return window (*Window 14*) is shown to sell approximately 32 hours faster than a listing with a no returns policy, *ceteris paribus*. A listing with a return window greater than 14 days (*Extended Window*) is associated with an approximate 153-hour reduction in the time to sale relative to a listing that does not permit returns. The two most predictive models (Models 2 and 5) also show that *Restocking Fees* are associated with an increase in *Time to Sale* of 43 hours. Free Return Shipping is not found to significantly impact *Time to Sale*.

Table 16: Second-Equation Regression Results

DV = Hours to Sale	Model 1 β (t)	Model 2 β (t)	Model 3 β (t)	Model 4 β (t)	Model 5 β (t)
Constant	1684.9107*** (19.33)	1699.0090*** (19.51)	1681.6845*** (19.230)	1691.9720*** (19.370)	1701.6696*** (19.50)
Landed Price[2]	1.0435*** (4.17)	1.0394*** (4.15)	1.0271*** (4.100)	1.0350*** (4.13)	1.0359*** (4.14)
Window 14	-30.9635** (-2.20)	-33.0297** (-2.35)	-32.0759** (-2.28)	-29.2037** (-2.07)	-32.2658** (-2.29)
Extended Window	-142.5465*** (-3.77)	-152.2356*** (-4.02)	-153.5244*** (-4.03)	-143.8224*** (-3.80)	-152.5873*** (-4.03)
Free Return Shipping	9.414 (0.11)	14.846 (0.17)	11.4544 (0.13)	10.5665 (0.12)	15.2235 (0.18)
Restocking Fee	29.422 (1.36)	43.0979** (1.98)	34.2479 (1.58)	28.1015 (1.30)	42.3057* (1.93)
Positive Threads	-0.2425** (-2.12)	-0.2474** (-2.17)		-0.2432** (-2.13)	-0.2476** (-2.17)
Neutral-Negative Threads	6.0983** (2.50)			7.0160*** (2.74)	
Neutral Threads		27.0760*** (5.06)			27.0759*** (5.06)
Negative Threads		1.284 (0.48)			1.7499 (0.62)
Service Recoveries	-9.4890** (-2.42)	-18.2428*** (-4.15)	-5.7967 (-1.17)	-8.5857** (-2.15)	-17.7117*** (-3.91)
Complaint-Free Threads			-0.0929 (-0.87)		
Trust-Revoking Complaints			2.8121 (1.03)		
Non-Trust-Revoking Complaints			-12.0503* (-1.67)		
Complaint Type Dispersion				-6.4306 (-1.19)	-2.6550 (-0.49)
Transaction Controls	Included	Included	Included	Included	Included
Product Controls	Included	Included	Included	Included	Included
R^2:	0.9293	0.9295	0.9293	0.9293	0.9295
Observations:	6519	6519	6519	6519	6519

* p<0.10, ** p<0.05, *** p<0.01

[2] Logged Landed Price is also used in a robustness check and the results are robust. See Ap. F for the full regression output.

In models 1, 2, 4, and 5, the count of feedback posts demonstrating positive satisfaction (*Positive Threads*) is negatively associated with *Time to Sale* at the 5% level. Thus, the more evidence of positive satisfaction in a seller's feedback history, the faster their products will sell. The combined count of posts with neutral or negative satisfaction (*Neutral-Negative Threads*) is positive and significant in models 1, and 4. That is, evidence of less than ideal customer satisfaction slows down sellers' sales rates. However, when disaggregate measures of neutral and negative satisfaction are included, only *Neutral Threads* is significant. This supports the conclusion of Rabby and Shahriar (2016) that neutral and negative satisfaction have different impacts, and therefore, disaggregate measures of satisfaction should be used instead of the combined measure, which has been in most studies on online reputations.

Models 1 and 2 are used to test if an inverse relationship exists between *Service Recoveries* and *Time to Sale* (H1b). After controlling for the *Landed Price,* the return policy, and the count of *Positive Threads* and *Neutral-Negative Threads,* the results in model 1, suggest that each *Service Recovery* reduces the *Time to Sale* by approximately 9.5 hours, on average. The results of model 2, which breaks out *Neutral Threads* and *Negative Threads* into separate measures, confirm the inverse relationship between *Service Recoveries* and *Time to Sale* and suggest an even stronger influence on *Time to Sale.* Thus, both models support **Hypothesis 1b**.

Model 3 is used to test **Hypothesis 2b**, which predicts a positive relationship between *Trust-Revoking Complaints* and *Time to Sale*. While the coefficient on Trust-

Revoking Complaints is positive, the relationship is statistically insignificant. Thus, support is not found for Hypothesis 2b.

Models 4 and 5 examine the relationship between *Complaint Type Dispersion* and *Time to Sale*. **Hypothesis 3b** predicts a positive relationship between these two variables. Like models 1 and 2, both the combined count of threads with neutral or negative satisfaction (*Neutral-Negative Threads*) and the disaggregate measures (*Neutral Threads, Negative Threads*) are used in models 4 and 5, respectively. In both cases, the coefficient on *Complaint Type Dispersion* is statistically insignificant. Thus, no support for Hypothesis 3b is found.

Results Summary

Table 17: Summary of Hypothesis Testing Results

Hypothesis	Independent Variable	Dependent Variable	Hypothesized Sign	Estimated Sign	Significance	Result
1a	Service Recoveries	Landed Price	Positive	Positive	99%	Fully Supported
1b	Service Recoveries	Time to Sale	Negative	Negative	99%	Fully Supported
2a	Trust-revoking Complaints	Landed Price	Negative	Negative	99%	Fully Supported
2b	Trust-revoking Complaints	Time to Sale	Positive	Positive	Insignificant	Not Supported
3a	Complaint Type Dispersion	Landed Price	Negative	Negative	95%	Fully Supported
3b	Complaint Type Dispersion	Time to Sale	Positive	Negative	Insignificant	Not Supported

The hypothesis testing results are summarized in Table 17. Ample support for the theoretical arguments of this study is found. The first-equation models provide support for Hypotheses 1a, 2a, and 3a. The regression results demonstrate that *Service Recoveries* are positively related to *Landed Prices*, while *Trust-Revoking Complaints* and *Complaint Type Dispersion* are inversely related to *Landed Price.*

The second-equation results support H1b; however, support is not found for H2b or H3b. *Service Recoveries* are shown to significantly reduce the time it takes for a listing to close, but no relationship is found between *Trust-Revoking Complaints* or *Complaint Type Dispersion* and *Time to Sale.*

In summary, four out of six hypotheses are supported by the empirical results, and they are shown to be robust to changes in the measurement of neutral and negative transaction satisfaction.

DISCUSSION AND CONCLUSION

Internet commerce suffers from substantial information asymmetry, and therefore, buyers must rely on signals, such as return policies and previous buyers' feedback to decipher the reputability of online retailers. This study classifies the feedback text of former buyers and develops reputational measures that current customers can use to make their buy or wait decisions for experiential consumer electronics products.

The results reveal that trust-revoking complaints that specifically describe a flaw in a seller's product or service have a highly significant, detrimental impact on landed price (supply) and time to sale (demand). This contrasts with non-trust-revoking complaints, such as nonspecific and unjustified complaints, which were found to have an indistinguishable impact on either dependent variable. This suggests that the focus of the complaint, described in the feedback text, influences the impact on buyer and seller perceptions and should not be overlooked. Therefore, numerical ratings do not provide a complete picture and only partially represent seller reputations.

Meanwhile, feedback documenting that a seller resolved an issue during the sale or post-sale was shown to have a beneficial impact on landed price and time to sale, regardless if the initial complaint was trust-revoking or not. Each successful service recovery was shown to increase the landed price by 0.23%. Since, the seller's complete feedback profile and hence the service recovery, is visible on all the seller's listings, the .23% increase applies to each of their listings. Furthermore, each service recovery is associated with an approximate 9.5-hour decrease in time to sale.

Variance of the complaint types in the feedback text (*Complaint Type Dispersion*) was found to have a significant impact on *Landed Price* but an insignificant impact on *Time to Sale*. Thus, buyers appear to focus on the number of neutral or negative feedback threads, whether those threads contain trust-revoking complaints, and evidence of service recoveries. Sellers, meanwhile, were found to significantly adjust *Landed Price* based on *Complaint Type Dispersion*. Perhaps, sellers have better

knowledge of their *Complaint Type Dispersion* than buyers and are therefore better able to utilize this information.

Limitations and Future Research

Future research could examine moderators of the relationships between complaint type, service recoveries, and demand. Since recent comments are likely to be more informative and relevant than comments further in the past, the timing of the complaint could moderate the relationship between the text content and its impact on time to sale. eBay classifies feedback into four categories: those that were written the month prior to listing creation, 1-6 months prior, 7-12 months prior, and over a year prior. These categories could be matched with the listing creation dates to identify the complaints available at the time of the listing creation and the recency of the available feedback posts.

The impact of the moderating role of buyer reputation on the relationship between feedback text and demand is another interesting avenue for future research. Buyer reputation could be measured by tenure on eBay or feedback scores, which are typically listed with feedback comments. More experienced buyers with higher reputation scores may be considered more trustworthy than their less experienced and lower scored peers, which increase the impact of their comments on future buyer behavior.

Additional pre-processing steps could also be conducted prior to the calculation of the category-specific dictionaries to improve the prediction accuracy. For example,

words could be sorted by frequency and those with extremely high or low frequencies could be removed. Automatic spell checking could also be applied to the text prior to the generation of the category-specific dictionaries and the text classification procedures. Additional scoring algorithms, such as the Robertson selection value, the relevance correlation value, and the document and relevance correlation score, could be applied to the tagged threads and their performance could be compared to the correlation coefficient scores. The impact of feedback text on other outcome measures, such as the probability of sale, is another promising avenue of research; as is, the impact from other perspectives, such as the effect of feedback on seller determined price.

Chapter 4: Return Policies, Feedback Text, and Firm Performance

OVERVIEW AND MAIN RESULTS

This dissertation is motivated by the ambiguity regarding the value of a lenient return policy and the implications of different types of buyer feedback on supply and demand in online retailing. While the potential existence of such relationships has been previously theorized, the author is unaware of any study that has empirically demonstrated the tradeoffs of a generous return policy and feedback history from both the seller and buyer perspectives. Using two unique datasets, gaps in the literature are addressed through the following research questions:

1. How do each of the components of retailers' return policies affect supply (landed price) and demand (time to sale)?
2. Does the impact of negative feedback on landed price and time to sale vary by complaint type?
3. Do successful service recoveries mitigate the negative impact of buyer complaints?
4. Does the variety of complaint types explain the non-linear impact of negative feedback?

These research questions are investigated through extensive analysis of landed price and time to sale for consumer electronic products in a popular online marketplace, eBay. Hypotheses are developed based on signaling theory, transaction cost economics, and procedural justice theory, and econometric and content analysis are used to

empirically evaluate each research question. Overall the empirical results present substantial evidence in support of the hypotheses. Table 18 summarizes the results.

Table 18: Summary of Main Results

Independent Variable	Dependent Variable	Result
Return Window	Landed Price	Significant
Free Return Shipping	Landed Price	Insignificant
Restocking Fees	Landed Price	Insignificant
Free Shipping	Landed Price	Significant
Return Window	Time to Sale	Insignificant
Free Return Shipping*	Time to Sale	Significant
Restocking Fees	Time to Sale	Significant
Service Recoveries	Landed Price	Significant
Trust-revoking Complaints	Landed Price	Significant
Complaint Type Dispersion	Landed Price	Significant
Service Recoveries	Time to Sale	Significant
Trust-revoking Complaints	Time to Sale	Insignificant
Complaint Type Dispersion	Time to Sale	Insignificant

* Values are based on the model with the logged seller-reputation measures

The results of the first essay suggest that the length of the return window is the primary determinant of the seller-determined *Landed Price*, while the presence of restocking fees significantly impacts demand through the *Time to Sale*. Thus, sellers incorporate the length of the return window into the overall prices they charge; however, customers pay the most attention to restocking fees and are particularly influenced by non-traditional restocking fees that require additional time and effort to identify. An extended return window, longer than the marketplace standard, is associated with an approximate 2-3% higher *Landed Price* than a no-returns policy; however, no association is found between an *Extended Window* and *Time to Sale*.

Meanwhile, a *Restocking Fee* of any magnitude is associated with a 9.87-hour increase in *Time to Sale,* but no association is found between *Restocking Fee* and *Landed Price*. Furthermore, non-standard restocking fees (*Restock Other*) had the largest impact on demand, prolonging *Time to Sale* by approximately 25.63 hours, on average.

The results also reveal a positive association between *Free Shipping* and *Landed Price;* however, an insignificant relationship is found between *Free Shipping* and *Time to Sale.* Since, the sample was restricted to completed (sold) listings, this positive association suggests that buyers are willing to pay a higher *Landed Price* to avoid losing the value of the initial shipping charge, which is nonrefundable in this setting; however, *Free Shipping* does not impact the time it takes to evaluate and complete the sale. Finally, partial support is found for the positive relationship between *Free Return Shipping* and demand. When logged seller-reputation measures were included in the model, the removal of return shipping charges and reduced *Time to Sale* by approximately 17 hours.

As to the impact of buyer feedback, the results of the second essay suggest that *Trust-Revoking Complaints* have an adverse impact on *Landed Price* (supply) and *Time to Sale* (demand), while other complaints, such as non-specific complaints and complaints about price, do not impact either dependent variable. This suggests that the content and focus of buyer feedback determines the impact on supply and demand.

Service Recoveries were also found to significantly improve both *Landed Price* and *Time to Sale*. Thus, high-quality sellers should focus on reducing the volume of trust-revoking complaints in their feedback history and should attempt service recoveries as often as possible. Since, service recoveries are visible across all of a seller's listings, this type of feedback has a compounding effect on the *Landed Price* and *Time to Sale* of many listings. With 100 sales at the average *Landed Price* from the sample of $356.25, each *Service Recovery* was shown to be worth $82 per month and lower the *Time to Sale* for each listing by 9.5 hours, on average.

Furthermore, *Complaint Type Dispersion* was found to negatively impact *Landed Price*, but no association was found with *Time to Sale*. Thus, sellers, are knowledgeable about their feedback profiles, and reduce the *Landed Price* of their listings when they have a variety of complaint types in their feedback profile. Buyers, meanwhile, appear to focus on the volume of *Trust-Revoking Complaints* instead of *Complaint Type Dispersion*.

The empirical models of the two essays are structurally similar, with both models including measures of return policy leniency, seller characteristics, product characteristics, and transaction characteristics. The difference being that the second essay substitutes new measures of seller reputation and quality, based on the text of the sellers' feedback profiles for the numerical ratings provided by eBay. In general, the conclusions of the first essay are verified by the results of the second, despite the use of the alternative reputation measures. The results confirm that an extended return

window results in a 2-3% price premium and that restocking fees have a stronger impact on *Time to Sale* than *Landed Price*. *Free Return Shipping* was not found to impact either *Landed Price* or *Time to Sale* in the second essay.

RESEARCH AND STRATEGIC IMPLICATIONS

This dissertation helps refine and enhance researchers' understanding of the relationships between return policies, feedback profiles, supply, and demand. It is among the first to empirically demonstrate the previously theorized notion that a generous return policy drives demand and influences pricing strategies, and it is the first to examine a highly competitive marketplace with fixed-price listings. This unique research setting is also used to extend prior knowledge by estimating the impact of several return policy components, which are shown to vary across buyer and seller perspectives. A potential mismatch is identified between the focus of buyers and sellers regarding return policy components. The length of the return window is shown to primarily affect *Landed Price* (supply), whereas restocking fees mainly impact *Time to Sale* (demand). Furthermore, buyers' strong, negative reactions to restocking fees counteract the benefits sellers generate with extended return windows. Additional research on the theoretical arguments underlying these distinctions as well as general buyer and seller perceptions of return policy components is suggested for future research.

Furthermore, this dissertation advances the work on reputational measures beyond numerical ratings and develops a classification process for quantifying buyer and seller

feedback. A distinction is made between trust-revoking and non-trust-revoking complaints, and a strategy is developed to quantify service recoveries and complaint type dispersion. *Trust-Revoking Complaints* are shown to negatively impact *Landed Price* and *Time to Sale*, whereas unspecific complaints and complaints about price (*Non-Trust-Revoking Complaints*) were shown to be unassociated with either variable. Thus, sellers should evaluate the focus of buyer complaints and focus their responses on those that will negatively impact demand.

In contrast to most studies on return policies and reputational measures in online retailing, the two essays of this dissertation examine both the buyer and seller perspectives of return policies and seller reputation within a highly competitive marketplace. In addition, a novel and extensive feedback classification process is used to generate a unique set of reputational measures that have not been previously studied. Since, the feedback analyzed in this study covers a wide range of product categories, the classifiers produced herein are directly applicable to other sellers on eBay. The general feedback classification process can be extended to many other settings where buyers provide feedback on sellers or their products. Examples include: other online marketplaces, such as Amazon, TaoBao, and EachNet, restaurant reviews, such as those on Yelp and Google, and hotel reviews, such as those on Kayak, Expedia, and Travelocity.

The results of this dissertation are not only interesting from a research perspective, but also have direct practical implications on managerial decisions. The results of the

two studies suggest that retailers can benefit from lenient return policies, service recoveries, and effective management of buyer feedback. Sellers in marketplaces where information asymmetry exist, such as online retailers, car dealers, auctioneers, and catalog retailers should evaluate their ability to process and handle returns as well as their ability to monitor and react to buyer feedback, and they should incorporate their strengths and weaknesses in these two areas into their price and demand forecasts. Sellers with strong service orientations, that are highly capable of handling product returns and correcting negative feedback, should signal their quality and the quality of their products with generous return policies, actively monitor buyer feedback, and attempt service recoveries. On the other hand, sellers that are less capable in these areas should adopt a price-oriented strategy and devote less of their attention to customer service.

LIMITATIONS AND FUTURE RESEARCH

While the empirical models in this dissertation clearly demonstrate the benefits of a generous return policy, including the use of an extended return window and free return shipping, the cost of these policies is not evaluated due to a lack of data on return rates and the costs of processing returns. This leaves open the question: Why aren't all sellers offering a generous returns policy? The fact that only a small portion of the sellers in the sample offer a generous return policy plays into the signaling argument. It may be the case that not all sellers are as capable, and therefore, the less capable sellers elect not to offer a generous returns policy because it is too expensive for them to do so. This supports the notion that a generous return policy is an effective signal;

however, the true value of the signal cannot be estimated without evaluating the cost of providing the signal. Similarly, without knowing the cost involved, it is impossible to ascertain the true value of monitoring buyer feedback and service recovery attempts.

Numerical analyses could be used to demonstrate the cost-benefit analysis of generous return policies and feedback monitoring. While information on sellers' return rates is not directly observed, the transaction outcomes evidenced in feedback threads were recorded as part of the feedback classification process for the second essay. Since "frequency of feedback is a good proxy for frequency of transactions" (Cabral and Hortascu, 2010, pp. 64), the percentage of transaction outcomes classified as a return, refund, or exchange could be averaged across all sellers to establish a baseline return rate for the numerical analysis. Furthermore, the deviation from the baseline return rate for each seller could also be calculated and included in the model. Literature-based estimates of return rates could also be utilized to verify and validate the feedback-based measures, and estimates from previous research could be used to approximate service recovery expenses. This cost-benefit analysis may reveal when it is appropriate to compete on both price and service and when it is more effective to compete solely on price.

It would also be interesting to examine if linkages exist between return policies and buyer feedback. For example, a lenient return policy may result in higher demand, which could produce additional buyer feedback. This feedback may reflect the seller's ability to manage product returns and could influence the future demand for the seller's

listings. The feedback produced by the seller's return policy decision could also affect the seller's future pricing and return policy decisions. Thus, an interesting avenue of future research is to examine the relationship between the seller's return policy decision (which rarely changes) and buyers' feedback related to their product return experience. Sellers with high-quality return processes or low return processing costs may benefit from this generous-return-policy-positive-buyer-feedback loop, which should put them at a competitive advantage in the marketplace. Conversely, sellers ineffective at handling product returns would be encouraged to limit or disallow returns.

Additional control variables could also be added to the models. While the degree of competition in the observed setting was high, with no less than 87 distinct sellers and 264 active listings for any of the six products over the observed period, the average number of competing listings at any given time could be calculated and used to explain some of the variation in *Landed Price* and *Time to Sale*. Additional seller characteristics beyond reputational measures could also be included in the models, such as a count of the product categories that the seller is competing in, the percentage of their overall sales that fall in the consumer electronics category, and the overall number of products they offer. In addition, *Time to Sale*, the (inverse) measure used as a proxy for demand, could be substituted with monthly sales volume per seller or the monthly revenue per seller, or a combination of either with *Time to Sale*.

Finally, the generalizability of this research could be extended to other settings. While the setting for this research has many desirable qualities in terms of the accuracy

and availability of data, the results may not be directly applicable to other settings. Even though return policies and buyer feedback are present in virtually every market, the results of this dissertation are limited to a single marketplace (eBay) and a single product category (expensive consumer electronic products).

Since return rates are typically greater for higher-priced items ($300-$500; Akturk et al., 2018, pp. 29), the new and expensive consumer electronic products studied in this dissertation may have a greater cost attached to a generous return policy. This may explain why so few sellers offer such a policy and why so many sellers do not allow returns. eBay's past as primarily a no-returns-allowed, auction platform may also have instilled unique institutional norms that influence its low return allowance rate.

Finally, the low return allowance rate in this marketplace may also be influenced by eBay's own Money Back Guarantee (MBG), which covers incorrectly described items, incomplete shipments, and broken or faulty parts. Since eBay's MBG already provides some protection for buyers, there is less incentive for average sellers to allow returns. However, as the results show, high-quality sellers can distinguish themselves within this marketplace with a generous returns policy and improve both *Landed Price* and *Time to Sale*. Thus, the precise impact of each return policy component may differ in other settings, and the overall impact of return policies is likely larger in settings other than eBay.

On the other hand, the results of the second essay are more generalizable. Extensive research has been conducted in recent years on the impact of numerical feedback ratings, verified reviews, expert reviews, and review timing. However, this dissertation is the first to quantify feedback text into complaint type categories, and it provides a process that could be extended to many other research settings. The classifiers (unigrams, bigrams, trigrams; see tables 32-39 in Ap. C) produced in this study could be directly applied to other sellers' feedback profiles on eBay or they could be used as a baseline or starting point for analyzing feedback in other marketplaces. The general feedback classification process could be replicated on other platforms, including Amazon, EachNet, Expedia, TaoBao, Travelocity, and Yelp.

Beyond the general limitations presented above, which are shared by both essays, specific extensions could be made to each individual essay. These are described in the next two subsections.

Essay 1 Extensions

Correlations were the primary focus of the supply (*Landed Price*) regressions; however, causality was of interest in the demand (*Time to Sale*) analysis, so endogeneity could be a concern. With less than 3% of sellers adjusting their return policies over the observed period, the sample demonstrates very low within-seller endogeneity. Since good instruments could not be found in the eBay setting, an exhaustive list of control variables were used to combat between-seller endogeneity.

Through extensive data collection efforts, variables from previous research as well as new variables tailored to the research setting were constructed and used to control for a seller-level omitted variable bias. An alternative approach that future research could follow is to examine exogenous factors, such as the return policy decisions of offline retailers and the return policy decisions of competitors with similar online reputations within and across product categories, to help explain sellers' initial return policy decisions.

Cluster analysis could also be used to identify different types of sellers. For example, one group of sellers may compete solely on price and may not allow returns. Whereas, another group may compete on a combination of price and service and offer a highly generous return policy, with extended return windows, free shipping, free return shipping, and no restocking fees. Other groups could be identified within these two extremes, and the group classification could be used to explain seller's initial return policy decisions and the efficacy of those decisions through a cost-benefit analysis.

Around the time of data collection, eBay sellers could highlight certain elements of their reputation or listing features with "why-to-buy" (W2B) displays. These displays highlight features such as extended return windows, free shipping, new product condition, seller experience, listing inquiries, previous sales, limited availability, and more. W2B options that highlight sellers' lenient return policies or reputation could amplify the relationships between return policy components, *Landed Price*, and *Time to Sale*.

Two dummy variables (*W2B-Reputation* and *W2B-Returns*) were created to account for prominent displays of seller reputation and lenient return policies on the listing page. *W2B-Reputation* takes a value of one if any of the following phrases appear in the three feature (W2B) displays: "100% positive feedback," or "Experienced seller." *W2B-Return* equals one if any of the following phrases appear in the three W2B displays: "30-day returns," "60-day returns," "Free shipping and returns," or "Hassle-free returns." These measures could be included in the regression analysis to control for the prominence of the return policy and seller reputation on the listing page and additional theory could be developed to explain the impact of these "signal moderators."

Methodological improvements include the use of a Cox proportional hazard model in the demand estimation. In such a model, the hazard would be the sale of the listing and the effect parameters would be the terms of sale (price, shipping charge, return policy). Based on the distribution of the time to sale variable, which is highly right skewed and is dominated by values less than 24 hours, the Cox model may be a more appropriate functional form.

To ease the interpretation of the return policy estimates, the return policy variables could be coded in an alternative manner. First, a dummy variable (*Return Allowance*) could be created to represent whether a return policy is offered (1) or not (0), regardless of the return policy specification. Then, three additional dummy variables could be

coded to account for whether an extended return window (*Extended Window*), free return shipping (*Free Return Shipping*), or restocking fee (*Restocking Fee*) is included (1) or not (0-including no returns). This coding scheme could test whether return allowance alone impacts *Landed Price* and *Time to Sale*. Each return policy would then be valued according to the sum of the coefficients associated with the policy and *Return Allowance*.

Furthermore, the disaggregate restocking fee measures could be recoded into a single continuous variable to enforce a linear structure on the percentage of restocking fee. The additional return restrictions in written (custom) return policies (*Restock Other*) that require buyers to open a new window and sift through detailed return policies, could be recoded as a *Return Policy Salience* dummy variable. The impact of restocking fee visibility could then be evaluated regardless of any conflicting percentage restocking fee values.

Seller-related controls other than the number of positive, negative, and neutral ratings over the previous twelve months could also be included in the empirical models. Particularly relevant are feedback measures related to item descriptions and shipping and handling, as these seller characteristics could impact the likelihood of having to make a return. Low communication scores could also reveal problems with sellers' returns management practices and could decrease the value of an extended return window or free return shipping.

Seller ability could also be controlled for with a variable (*Title Skill*) that captures sellers' ability to include "attractive words" in their titles or subtitles (Lei, 2011; Shang et al., 2017b). This variable could be coded 0-4 by searching the listing titles for phrases related to (1) the speed of shipping/handling, (2) the new/sealed condition of the product, (3) a positive seller reputation, or (4) elevated demand.

The product-related controls could be strengthened with the addition of product popularity measures. As shown in table 24 in Appendix B, the *Metascore* and *User Score* from Metacritic.com were recorded for each of the products, including the special edition Xbox One models. The addition of these variables could explain some of the variation in *Landed Price* and *Time to Sale* and provide more accurate estimates of the variables of interest.

Finally, non-sales could also be included in the supply (*Landed Price*) equation to better represent the equilibrium price in the market. By doing so, the sample size and explanatory power of the supply equation would increase, providing more accurate estimates. The explanatory power of the demand equation would remain unchanged, because the *Time to Sale* for those listings would remain unobserved.

Essay 2 Extensions

One limitation of the second essay is that all feedback threads are treated equally, regardless of the timing of the posts. Up to 1,000 feedback threads are recorded for each seller, and no distinction is made between threads that occurred within the past

month and threads that took place over a year prior to sale. Since recent comments are likely to be more informative and relevant than comments further in the past, the timing of the complaint could moderate the relationship between the text content and its impact on *Time to Sale*.

eBay publicly lists the recency of feedback posts into the following categories: within 30 days, 31-180 days, 181-365 days, and 365+ days from the date of observation and this information was collected for each feedback post at each data collection period (see table 19 in Appendix B for the list of dates). The feedback posts were also recorded in chronological order, which can provide additional information on the timing of each post. This information could be used to develop a time series analysis of seller's feedback profiles, which could demonstrate the short and long-term effects of complaints and service recoveries.

The moderating role of buyer reputation on the relationship between feedback text and demand is another interesting avenue for future research. Buyer reputation could be measured by tenure on eBay or feedback scores, which are typically listed along with feedback comments. More experienced buyers with higher reputation scores may be considered more trustworthy than their less experienced and lower scored peers, which should increase the impact of their comments on future buyer behavior.

From a methodological standpoint, additional pre-processing steps could be conducted prior to the calculation of the category-specific dictionaries to improve

prediction accuracy. For example, words could be sorted by frequency and those with extremely high or low frequencies could be removed. Automatic spell checking could also be applied to the text prior to the generation of the category-specific dictionaries and the text classification procedures. Additional scoring algorithms, such as the Robertson selection value, the relevance correlation value, and the document and relevance correlation score, could be applied to the tagged threads and their performance could be compared to the correlation coefficient scores.

The impact of feedback text on other outcome measures, such as the probability of sale, is another promising avenue of research. For example, complaint types, such as *Black-Market Complaints*, *Misrepresentation Complaints*, and *Quality Complaints*, may have highly detrimental effects on probability of sale, while *Delivery Complaints* and *Communication Complaints* may have less of an impact. An analysis of probability of sale may require further distinctions beyond *Trust-Revoking Complaints* and *Non-Trust-Revoking Complaints*.

Other measures of *Complaint Type Dispersion* could also be tested. For example, alternative measures could include the standard deviation and coefficient of variation of complaint types per seller or a variant of the Herfindahl-Hirschman Index (HHI). These measures could be used to test if feedback profiles highly skewed towards one or more types of complaints have a greater negative impact on *Landed Price* and *Time to Sale* than profiles that are evenly dispersed across complaint types.

Finally, the variable *Non-Trust-Revoking Complaints* could be disaggregated into *Price Complaints* and *Unspecified Complaints* to test if either type of non-trust-revoking complaint significantly impacts *Landed Price* or *Time to Sale.* An argument could be made that *Price Complaints* cause sellers to adjust their landed price downward to avoid future complaints about price or cause buyers to delay their purchase at the current price and increase their product search. Disaggregate measures of non-trust-revoking complaints could be used to test this hypothesis.

Overall, this dissertation offers strong evidence on the value of a generous return policy and the advantages of managing and reacting to buyer feedback. The analysis of individual return policy components and the novel complaint categorization process can be applied to many other settings and offer many future research opportunities.

Appendix A: Selling on eBay

The selling conditions on eBay are constantly evolving, with new listing options, site features, and policy changes occurring frequently. This Appendix attempts to describe the process for listing and selling products and the development of feedback profiles. Sellers' listing format, return policy, shipping service, and why-to-buy options are all discussed. The process for creating a store and the advantages of doing so as well as the qualifications and requirements for earning badges, which are another useful set of reputational signals used on the platform, are presented. Finally, the post-purchase processes for collecting feedback are described in detail.

LISTING OPTIONS

Format

eBay offers multiple listing formats, from pure auctions to fixed price listings to hybrids (eBay, 2018). In its earliest years, eBay was dominated by the auction format; however, the fixed price, Buy-it-Now (BIN) format has grown in popularity and now represents 80% of all listings on the site (Stevens, 2016).

Auctions

In the traditional auction format, sellers list their product(s) for sale, collect bids for a fixed length of time, and sell to the highest bidder. Buyers can watch the item to monitor the bidding process, and once the listing closes, the highest bidder wins the item and completes the purchase.

Fixed Price

The fixed price, BIN format is the simplest way to price products on eBay (eBay Customer Service, 2018). A single list price is offered, and customers can purchase the product(s) immediately without having to wait for the end of a bidding period. Note that sellers must have a feedback score of at least ten to use the BIN format.

Hybrids

Hybrid formats also exist where the BIN option appears within eBay auctions and where offers can be made on BIN listings. There is no additional charge for the hybrid formats. Adding the BIN option to an auction allows buyers to purchase the item(s) right away at the BIN price before the bidding begins. Generally, the BIN price must be 30% higher than the auction price, and the BIN option is removed as soon as someone bids on the item(s). (This has since been changed to a delayed removal.)

When "Let buyers make offers" is selected under the format and pricing tab of the advanced listing form (eBay, 2018d), sellers allow bids below their BIN price, and the "Make Offer" link appears below the BIN price in the listing. Buyer offers exist for 48 hours, and the sellers can review and accept them or make counteroffers below the BIN price. Note that these offers are for the product(s) only and do not include shipping. The buyer can also specify additional terms as part of the negotiation process (such as the submission of additional product information and/or images or alternative shipping services.

Return Policies

Sellers' Return Policy Options

eBay sellers can customize their return policies in multiple ways. If the seller chooses to permit returns, then they must specify four components. First, they must select a return window (the maximum number of days from the buyer's receipt of the product and the return request). Three standard options are available: 7 days, 14 days, 30 days, and 60 days. (Prior to the observed period, a 3-day option was also a standard option.)

Second, the seller determines how refunds will be allocated. Three standard options exist: "money back," "money back or replacement (buyer's choice)," and "money back or exchange (buyer's choice)". Next, the party that is responsible for paying the return shipping, either the buyer or seller, is selected. Finally, any restocking fees are specified. The standard options are 10%, 15%, and 20%.

There is also space to specify additional return policy details, where the sellers can essentially input any custom value for the four components listed above as well as additional restrictions, such as unopened conditions.

The seller's return policy is frequently displayed throughout a transaction. For example, return policies are displayed on the listing page directly under the price and shipping information, in the confirmation email under order details, and on the packing slip (when specified by the seller).

eBay Money Back Guarantee

Even when sellers select "no returns accepted," the eBay platform protects the buyer from certain conditions under its "eBay Money Back Guarantee" (eBay Customer Service, 2018; eBay, 2018). This policy covers incorrectly described items, incomplete shipments, and broken or faulty parts. It does not however, cover returns due to dissatisfaction, which fall under the return policy of the seller. Buyers can also request eBay to act as an intermediary for disputes lasting longer than three business days, and they can expect a resolution in 48 hours or less. In most cases, the eBay MBG favors the buyer.

Shipping Services

Sellers can customize their options for domestic and international shipping. For domestic shipping they have four options.

1. Flat: same cost to all buyers
2. Calculated: Cost varies by buyer location
3. Freight: large items over 150 lbs.
4. No shipping: Local pickup only

When the Calculated shipping option is used, the exact rate depends on the distance between the buyer and seller and these rates are accessible to the buyers from a link on the listing page. The Flat shipping option lists a common charge applicable to all

buyers. Under both options, the exact shipping charge is recorded at the time of sale. The Freight and No shipping options were not observed in the sample.

The default shipping service on eBay is Economy, which equates to 2- to 9-day delivery window. Sellers can also select from Standard (1-5 days), Expedited (1-3 days), and Overnight (1-day) services or offer free shipping.

Why-to-Buy Displays

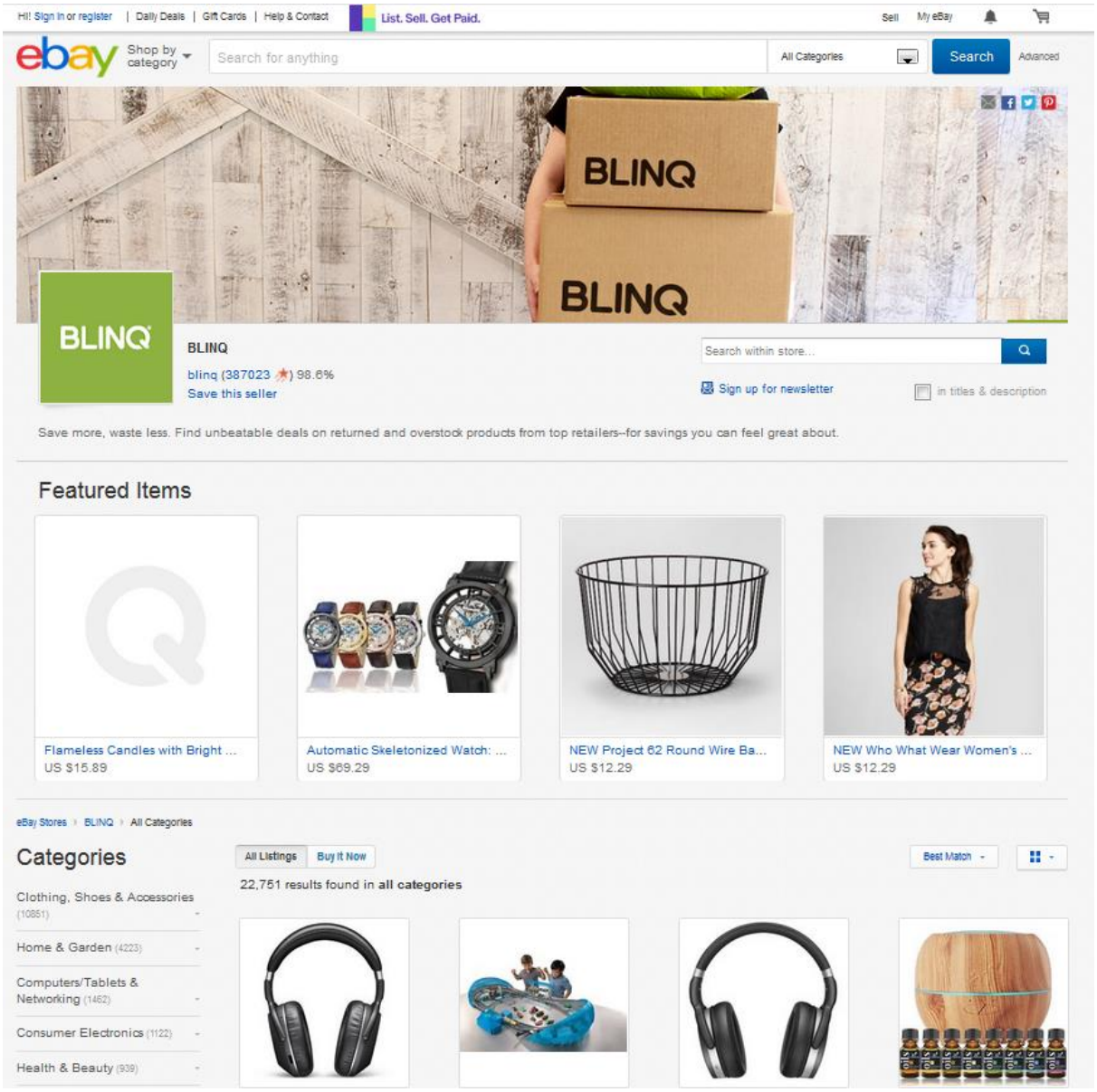
At the time of data collection, eBay sellers could highlight certain elements of their reputation or listing features with "why-to-buy" (W2B) displays. These displays could be used to highlight features, such as extended return windows, free shipping, new product condition, seller experience, listing inquiries, previous sales, limited availability, and more. Up to three W2B displays could appear on a single listing page; however, sellers did not have to use all three and could instead highlight one or two aspects of their listing within the same area on the page. Displays that highlight seller reputation and lenient return policies are relevant to this research, and therefore, two dummy variables were created: *W2B-Reputation* and *W2B-Return*. *W2B-Reputation* takes a value of one if any of the following phrases appear in W2B displays on the listing page: "100% positive feedback," "Experienced seller." *W2B-Return* equals one when any of the following phrases appear: "30-day returns," "60-day returns," "Free shipping and returns," or "Hassle-free returns." Over time, new W2B signals have been added, and eBay has since taken control of theW2B options and uses machine learning to optimize the displays for each customer.

Stores

Sellers can also signal their quality through the ownership of an eBay "store," which allows them to organize and promote their listings on a single page. Stores can also be used to promote brand loyalty through seller-specific product categories, exclusive promotions, and newsletters.

The store page for Blinq, one of the largest (by feedback volume) sellers in the sample, is shown in Figure 4. The page clearly indicates that Blinq is large volume seller, with 22,751 active listings across multiple categories (e.g. consumer electronics, home and garden, clothing, shoes & accessories).

Figure 4: Example "Store" (Seller ID=Blinq)



Other Options

Additional features can be added to the listing pages, including some free options and some (e.g. subtitles) at extra cost. Sellers can allow buyers to add their listings to "watch lists" and receive updates on price changes, bids, and sales over time. This option is freely available to all sellers. eBay sellers can write product descriptions of up to 4000 characters.

Every listing on eBay must include at least one image of the product. The first image that is added is called the "gallery photo" and appears next to the item's title in search results and on the listing page. Up to twelve images can be added for free, and these images appear as thumbnails under the gallery photo on the listing page. Additional images can be added to the product description area of the listing, but they must be hosted online on a photo sharing website, such as Photobucket.com.

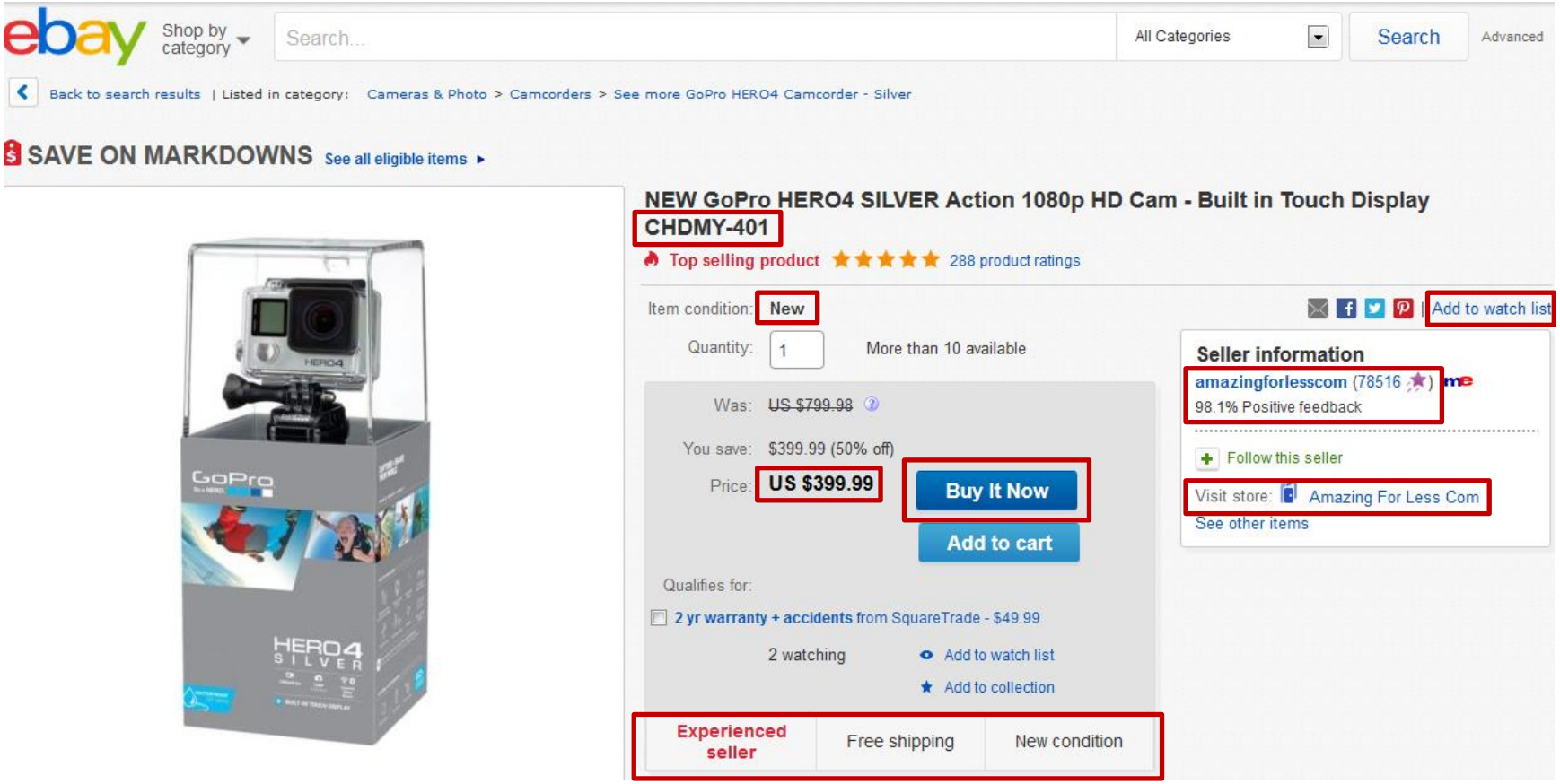
AN EXAMPLE LISTING

See Figure 5 for an example listing of the GoPro Silver Moto Bundle. First, notice that the product can easily be identified by its manufacturer part number (MPN=CHDMY-401), which appears in the listing title. The item condition is clearly listed as "New" and the listing is in the fixed-price, Buy-It-Now (BIN) format. Without the "Make Offer" option on the page, there is no opportunity to make a bid, and therefore, customers must accept the BIN price ($399.99) to purchase the product.

Second, notice that this is an experienced seller with an eBay feedback score of 78,516 and 98.1% positive feedback overall. The “purple shooting star” next to the feedback rating indicates that this seller (amazingforlesscom) is in the second highest tier of sellers with respect to buyer feedback ratings (eBay, 2018). The seller also owns an eBay store and uses all three Why-to-Buy displays to promote their tenure (“Experienced Seller”), shipping service (“Free Shipping”), and product condition (“New Product”).

Third, notice that a *Watch List* option exists for the listing. There are also links to the seller’s feedback profile and its store. 288 product ratings exist for this product, as of May 24, 2018; however, this is a new feature to eBay that did not exist at the time of data collection.

Figure 5: Example Listing Page for the GoPro Silver Moto Bundle



POST-PURCHASE

Payment and Delivery

After purchasing the product(s), an email confirmation is sent to the buyer, who has two days to pay the seller. The seller ID, item title, quantity, price, tax (paid to the buyer's state), and shipping and handling information all appear on this invoice. An additional reminder email to pay is sent within 48 hours if the buyer does not pay within the required period. Delays beyond 48 hours are at the discretion of the seller and are eligible for a cancellation request.

Once the seller receives payment, they must ship the product(s), along with a packing slip, according to the shipping and handling options of the listing. If the seller is unable to fulfill the order (e.g. the item was damaged or is no longer in stock), then the seller can cancel the transaction within 30 days, even if the buyer has already paid. Non-delivery without a cancellation, however, violates eBay's user agreement and is considered one form of fraud by the Internet Crime Complaint Center (IC3) and the FBI. It is also considered fraud when the seller falsely claims the item was damaged or no longer in stock.

Handling Returns

Upon receipt of the item(s), the buyer has the number of days specified in the listing's return window to initiate a return. The seller then has three days to respond to this return initiation request before eBay can step in and act as an intermediary. Once

a return has been accepted, the buyer has five days to ship the return (although this policy is rarely enforced).

EBAY FEEDBACK FORUM

The eBay reputation system, also known as the Feedback Forum, is vital to the success of eBay (Resnick et al., 2000). Feedback ratings are linked to each member and displayed in brackets next to the user ID throughout every transaction on the site and on all deliveries, if requested. To sell on eBay, users must also make their feedback comments public. Buyers can hide their feedback comments; however, their overall ratings (i.e. number of positive, neutral, negative) are always displayed.

Seller Ratings

Post-sale, buyers can leave feedback on the seller for up to 60 days after the transaction. These ratings can be positive, neutral, or negative and include short comments ("Quick service; faster than anticipated;" "Seller handled problems quickly and politely"), which can be revised in the case of a mistake or service recovery. In the case of a revision, the revised feedback replaces the original feedback, and the post is automatically marked with the line "Feedback was revised by the buyer."

If the buyer leaves malicious or provably dishonest feedback, then the seller can contact eBay to request its removal. If eBay agrees that the feedback is unwarranted, then the post is replaced with the line "This comment has been removed by eBay. Learn

more." The numerical rating (1,0,-1) that the buyer provided is also removed from the seller's feedback score.

If the seller believes they have resolved an issue after the buyer has left their feedback, then the seller can request a feedback revision (eBay, 2018). This triggers an email to the buyer with the seller's message requesting the revision. The buyer then has ten days to either agree and revise the feedback or disagree and state a reason. Only one revision request is permitted per transaction and five revision requests are allowed for every 1,000 feedback comments received in the past 12 consecutive months. However, high volume sellers (with 1,001+ feedback comments per year) can submit additional requests.

Buyers can also leave anonymous feedback on the seller's item description, communication, shipping time, and shipping and handling charges at the same time they leave an overall feedback rating and comment (eBay, 2018). These detailed seller ratings do not contribute to the seller's feedback score, but they are publicly available on each seller's feedback page. These ratings can be revised by the buyer within 30 days.

Buyer Ratings

After each transaction, sellers can give buyers either positive or neutral ratings and leave short comments (e.g. "Thank you for your business; highly recommended buyer.") Negative feedback is not permitted to avoid retaliatory negative *ratings* from

the buyer. However, retaliatory *comments* are a very common response to negative buyer feedback. Once the seller's feedback is submitted, it cannot be edited or taken back.

Product Ratings

During data collection, no product reviews were available on eBay; however, they were introduced to a limited set of product categories with the Fall 2016 Seller Updates. The reviews appear at the bottom of the listing page (however, a star rating and hyperlink to these reviews exists under the listing title) and are meant to identify any design and functionality flaws of the product.

Product reviews could initially be found across product condition and seller, resulting in substantial backlash from the eBay community, with sellers reporting that the reviews contained "erroneous, misleading, and dysfunctional" information (The eBay Community, 2015). For a short period of time, sellers could elect to remove product ratings from their listing pages through the "site preferences" options; however, this option was removed on May 25, 2016.

In response to the initial criticism surrounding product reviews, the supplemental information provided alongside each product review was expanded in Spring 2016 to include the item condition of the item reviewed, the item ID purchased, seller ID when available, and reporting options for inappropriate content (eBay, 2016).

Appendix B: Data Collection and Cleaning

DATA COLLECTION

Over a seven-month span, a structured web-crawling procedure was used to collect data on transactions involving consumer electronic products sold on the eBay marketplace. Three products were selected: the Microsoft Xbox One entertainment system (Xbox), the GoPro Hero4 action camera (GoPro), and the Bose Quiet Comfort 25 (QC25) headphones (Bose). These products were homogeneous and standardized, with few options for customization, which minimized the risk of feature-specific confounds.

The data collection process is depicted in Figure 6 and the web crawling execution times and frequency of listings compiled during each run are listed in table 19. First, information on each completed listing was compiled using the eBay advanced search page[3] with keywords "xbox one," "gopro hero 4," and "bose qc25." The search was restricted to new products and fixed-price (buy-it-now; BIN) listings offered by sellers located in the U.S. using the buying format, condition, and sellers search options. The listing start times were recorded directly from the search results and the listing-specific item IDs were extracted from the source page. The listing URLs were also recorded from the search results and used to gather the listing characteristics (price, shipping

[3] http://www.ebay.com/sch/ebayadvsearch

cost, return policy, etc.), purchase history URLs, and seller URLs, which were used in the second stage of the script. The purchase history URLs revealed information on the quantity purchased, price paid, purchase time, and buyer ID and feedback score. Most of the sales (99%) were for a single quantity, and the average prices reflect those of the most recent listings.

Next, the seller reputation measures (e.g. numerical reputation measures, text comments from buyers, etc.) were collected through the seller URLs. The retailer feedback page associated with each seller URL contains extensive information on each retailer, including the date that the seller ID was created, their aggregate feedback score, counts of their positive, negative, and neutral reviews, text comments from buyers, and links to the listing pages of their recently sold items. A maximum of one thousand feedback comments per seller were collected, and only the comments received as a seller were recorded (i.e. comments for the retailer acting as a buyer were excluded).

In the final stage of the script, information on the recently sold items with feedback was recorded through the recent feedback URLs, which were displayed as "View Item" hyperlinks next to the most recent feedback comments. These links only exist for 90 days and include information on the item sold by the seller, item-level product category, sale price, quantity purchased, product condition, purchase time, and buyer feedback score and (partially hidden) buyer ID. The return policy at the time of sale was also recorded, when available.

Figure 6: Data Collection Process

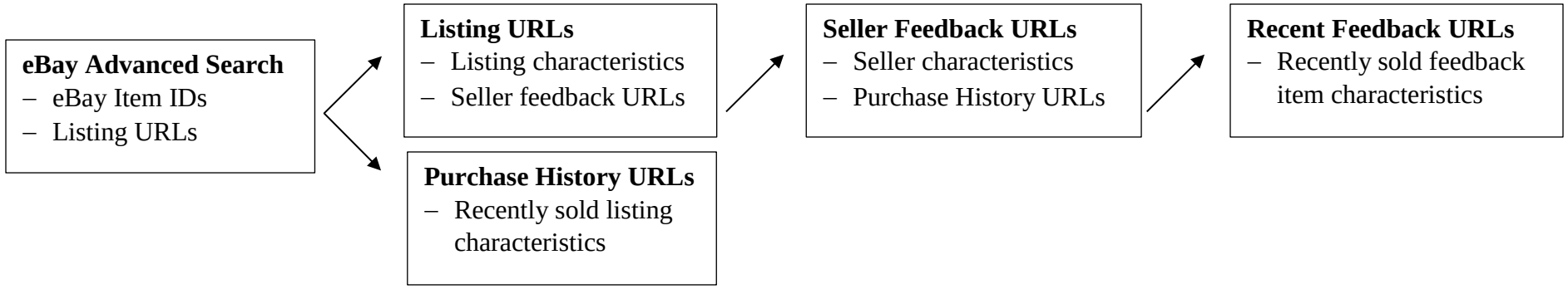


Table 19: Web Crawling Execution Times and Frequency of Listings

Date	Time	Freq.	Percent
5/16/2015	0:28:07	5,436	21.90
6/15/2015	15:21:20	2,645	10.66
7/15/2015	22:24:13	2,879	11.60
9/15/2015	22:08:00	4,319	17.40
10/16/2015	23:38:22	1,911	7.70
11/19/2015	6:32:31	7,634	30.75

N=24,824

Duplicate Records

Since the web-crawling script compiled the complete set of sold (unsold) listings over the previous 90 (30) days, and it was executed monthly, duplicate sales were recorded. Two methods were used to check for duplicate records. Duplicate records were identified at the broadest level and at the listing ID level. At the broadest level, records were tagged as duplicates if and only if, every one of the variables had identical values. Additional records with repeat listing-ID values were also tagged as duplicates in a subsequent search. This eliminated duplicate observations that were not eliminated in the previous check due to missing values not recorded by the web crawling script.

Missing Values

Web-crawling scripts are vulnerable to deviations from the standard placement of items on the page. Minor variations, due to the length of a string or the addition of a logo, can result in missing observations. The structured web-crawling script used here for data collection is susceptible to these deviations, and as a result some observations with missing values had to be removed.

DATA CLEANING

Three standardized versions of the Bose QC25 headphones were offered (Black, White, and Triple Black) with the only difference being the color of the exterior and interior pads, and all three models were launched with a manufacturer suggested retail

price (MSRP) of $299.95. Note that the Bose QC25 headphones were also offered in nearly unlimited combinations of colors, and these are all categorized as “Bose Custom” in the sample, along with the Triple Black edition.

The initial launch of the Xbox One entertainment system (on November 22, 2013) was paired with the Kinect video sensor (MSRP=$449); however, later models were offered without the Kinect at a reduced price (MSRP=$349).

The GoPro Hero4 Black and Silver edition cameras were launched on September 29, 2014 at $499.00 and $399.00, respectively, and the Hero4 Session edition camera (a discount model) was launched on July 10, 2015 with a MSRP of $399.99. Images of the eight base products appear in Figure 7. Note that the “Triple Black” edition of the QC25 headphones is presented in the Bose Custom category, since it is the most common color combination in that category.

Figure 7: Images of Standard (Base) Products

Bose Black

Bose Custom

Bose White

Xbox One without Kinect

Xbox One with Kinect

GoPro Black

GoPro Session

GoPro Silver

Data Screening

The initial data screening process consisted of a combination of text analytics and manual search. Text analytic procedures were used to tag any models that deviated from the following assumptions:

A1. New product(s)
A2. US buyer and seller transacting with US currency ($)
A3. Fixed-price listing
A4. Standard model with all accessories included

Used and Open-Box Listings

Listings were marked and subsequently dropped if any of the following phrases (or their case variants) appeared in their title:

> *day(s) old, like new, month(s) old, new other, open box, opened, (manufacturer) refurbished, resealed, used, week(s) old, year(s) old*

Listings titles with keywords "*new,"* "*only*" and "*sealed*" were also marked and manually checked as were titles with the phrases "*not opened*," "*seal is not broken*," "*sealed is not broken*," and *"unopened.*" A search for commonly used acronyms related to product condition (see table 20) also helped to distinguish between new and complete product listings from used and/or incomplete product listings (eBay, 2009; eBay, 2018).

Table 20: Acronyms used on eBay to Describe Product Condition

Acronym	Meaning	Acronym	Meaning
AUTH	Not quite authentic	MNT	Mint
BN	Brand new	MWBMT	Mint with both mint tags
BNIB	Brand new in box	MWBT	Mint with both tags
BNS	Brand new sealed	MWMT	Mint with mint tags
BNWT	Brand new with tags	MYO or M.Y.O.	Million years old
DLX	Deluxe	NDSR	No dents, scratches, or rust
EUC	Excellent used condition	NBW	Never been worn
EXC	Excellent	NC	No cover
F	Fair	NIB	New in box
FAUX	Not a genuine item (faux pearl)	NIMSB	New in manufacturer's sealed box
FC	Fine condition	NIP	New in package
FS	Factory sealed	NM	Near mint
FUBAR	Fouled up beyond all recognition	NOS	New old stock
G or GC	Good condition	NRFB	Never removed from box
GU	Gently used	NWOB	New without box
HTF	Hard to find	NWOT	New without tags
LN	Like new	NWT	New with tags
MIB	Mint in box	OOAK	One of a kind
MIBP	Mint in blister pack	PC	Poor condition
MIMB	Mint in mint box	SAIS	Sold as is
MIMP	Mint in mint package	SS	Still sealed
MIOP	Mint in open package	SW	Slight wear
MIP	Mint in package	VF	Very fine condition
MNB	Mint no box	VG or VGC	Very good condition

Foreign Transactions

To avoid cultural differences in the perception of return policies, the sample was restricted to US sales conducted with US currency. Thus, if either the buyer or the seller was located outside of the US or if foreign currency was used in the transaction, then the listing was tagged and removed.

The listings were tagged if the "item location" did not include "*United States;*" if the "shipping cost" included "*AU*", "*C*", "EUR", "GBP", "SGD", "MYR", "PHP", or "INR", or if the "shipping service" was any of the following:

> *AusPost Air Mail Parcel*
> *AusPost Express Courier International*
> *Economy Shipping from outside US*
> *Expedited Int'l Shipping*
> *Expedited Shipping from outside US*
> *International Tracked Postage*
> *Other Shipping*
> *Small Packets - International - Ground*
> *Standard Int'l Shipping*
> *Standard Shipping from outside US*

Based on these conditions, 328 foreign sellers were found, and 11 foreign buyers were identified, reducing the sample size by 339 observations.

Best Offer Listings

As described in Appendix A, eBay sellers can permit customers to bid on their fixed price listings. This "hybrid" format can increase the sellers' chances of selling their product(s) by allowing customers to negotiate, but it may result in a lower sales price. To avoid complications associated with this hybrid format, listings that indicate the "best offer price was accepted" were removed from the sample. For example, if the web-scraped data indicated that the closing (sale) price was the following, then the listing was dropped from the analysis:

> *[US $96.00Best offer price was accepted]*

A search for "*Best offer price*" was used to identify and remove these 1,077 listings that violated assumption (A3).

Missing Items

Some listing titles clearly stated that items were missing from the standard package.

> *accessories only, accessory only, bag only, box only, cables only, camera only, camera only, console only, console unit only, controller only, controller only, DLC only, game(s) only, HDMI only, inserts only, no box, no controller, no cords, no Elite controller, power adapter only, replacement unit, Xbl only, without (box)*

Unsold Listings

Because every listing change, results in a new listing ID, even minor changes, like a $0.50 reduction in the price, are considered unsold. The sample is also cutoff on the final web-crawling execution date, which could potential bias the time to sale estimates. As a result, the listings that did not result in a sale were removed prior to the analysis.

Product Identification

As mentioned previously, a combination of text analytics and manual search were used to identify the products from the listing titles. As the listing titles were manually read, a list of product identifiers (keywords and phrases) was created. This list included words commonly found in the listing titles as well as numeric and alphanumeric identifiers provided by the company, such as the Manufacturer Part Numbers (MPN), and barcode symbols, such as the Universal Product Codes (UPC-A) and European Article Numbers (EAN-13).

This list combined with text analytics was used to narrow down the possible range of products in each listing. This was followed by another round of manual product identification and a revision of the list. The process was then repeated until all listings had been categorized by their contents. A similar procedure was later conducted to identify the inclusion of any accessories. The following subsections identify the keywords used for each product.

Bose Models

Little variation beyond the color of the inner cushion and the outer pads was found for the Bose QC25 headphones. Thus, the following set of terms (and their case variants) was used to identify the color of the Bose QC25 headphones:

Bose Black: Black, Blk, Black/gray

Bose White: White

Bose Custom: beige, blue, brown, custom, gold, green, silver, tan, teal, triple black, triple blk

Listings titles that included both Bose Black and Bose White terms (e.g. black, white) terms were removed due to the inability to distinguish amongst the products included in the listing.

GoPro Models

The contents of the GoPro and the Xbox listings had significant variation. The GoPro was often bundled with accessories and attachments and "Special Edition" Xbox

models were offered in many cases. Therefore, multiple rounds of data cleaning were necessary to pinpoint the contents of those listings.

For the GoPro listings, the models were first identified, and then the presence of attachments and accessories were accounted for. The following terms (and their case variants) were used to identify the model of the GoPro camera:

GoPro Black: Black, Blk

GoPro Silver: Silver, Sliver

GoPro Session: Session, Sesion

In addition to the common words listed above, manufacturer provided identifiers (MPN) and barcode symbols (UPC-A) were used for product identification. MPN values are specified by each manufacturer and used to unambiguously identify a model and its design within a corporation. Each part the manufacturer makes has a different MPN and each manufacturer uses a different combination of letters and numbers to identify their parts. Thus, identical parts produced by different manufacturers can be identified by their MPN. Similarly, the 12-digit UPC-A barcodes are uniquely assigned to trade items (following the GS1 specification gs1us.org) and used to track items throughout supply chains and at the point of sale. Since these values are highly standardized, they were very useful for matching the exact model of the GoPro and Bose products. Again, the contents of the Xbox listings varied considerably, so the product identifiers were less useful for those listings. A combination of manual search, common keywords, and MPN were therefore used to identify the Xbox models.

The identifier values associated with each of the GoPro and Bose products as well as the Manufacturer Suggested Retail Price (MSRP) at the time of product launch are provided in table 21. Note that the Amazon Standard Identification Numbers (ASIN) are also listed for reference purposes, although they were not used in any of the listing titles. The EAN-13 values are not listed, because they are equal to the UPC-A values with an additional leading zero in all six cases.

The identifiers were drawn from the official manufacturers' listings on Amazon.com (e.g. amazon.com/Bose-QuietComfort-Acoustic-Cancelling-Headphones/dp/B00VW7U8SY?th=1) and from upcitemdb.com (e.g. upcitemdb.com/upc/17817699037) and finally verified at barcodelookup.com. The MSRP values were taken from company press releases (e.g. https://globalpressroom.bose.com/us-en/pressrelease/view/1300). Note that the identifiers for the Bose Black and White models are the Samsung/Android versions, which were the standard. There were also Apple compatible editions of the Bose headphones with different UPC-A and ASIN values. Those identifiers were also searched to help pinpoint the color (i.e. Bose Black, White, Custom); however, no distinct was made beyond that in the analysis. The MPN were identical for the Apple and Android models. Note also that the Bose Custom identifiers correspond to the "Triple Black" headphones the most popular custom model.

Table 21: Bose and GoPro Identifiers

Product	MPN	UPC-A	ASIN	MSRP
Bose Black	715053-0010	017817699099	B00VW7U8X4	$299.95
Bose Custom	715053-0030	017817701396	B0117RFP0Y	$299.95
Bose White	715053-0020	017817699037	B00VW7U8SY	$299.95
GoPro Black	CHDHX-401	818279012767	B01FIL2X7I	$499.00
GoPro Session	CHDHS-101	818279014266	B010H05JMQ	$399.99
GoPro Silver	CHDHY-401	818279018790	B01M0MKNK6	$399.00

Note: MPN is also known as the Model #, Mfr Part #, and MFR.

As table 21 shows, the launch price of the Bose QC25 headphones was $299.95, regardless of color. The QC25 headphones were also the cheapest base product in the sample.

Xbox Models

The original Xbox One model launched on November 22, 2013 and included a black 500 GB console, the Kinect sensor, the official Xbox One chat headset, a black wireless controller, 2 AA batteries, a HDMI cable, and a power supply. Approximately six months later, another model was released without the Kinect sensor and the chat headset. Variations in the color of the console began on October 28, 2014 with the release of the "Cirrus White" Sunset Overdrive special edition; upgraded hard drives were introduced on November 3, 2014 as part of the Call of Duty: Advanced Warfare special edition; finally, a 1 TB solid state hard drive (SSD) model, named the "Elite" edition, was introduced on December 1, 2015. Many Xbox One consoles bundled with digital/physical copies of specific games have also been released over time.

The contents of the Xbox listings in the sample were highly variable, and required multiple stages of product identification in order to distinguish between hard drive size, and appearance, as well as the inclusion of the Kinect sensor, Xbox Live subscriptions, and popular games. In the first stage, text analytics and manual search were used to identify hard drive capacity, and the inclusion of the Kinect sensor and Xbox Live subscriptions.

The Xbox One has two options for hard drive (HDD) capacity: 500 gigabyte (GB) and 1 Terabyte (TB). The standard edition model includes a 500 GB HDD and the 1 TB option is an upgrade that was often included in the special edition packages. In fact, the COD:AW, Elite, Fallout 4, Fifa 16, Forza 6, Halo Guardians, Madden NFL 2016, and Tomb Raider models all included the 1 TB HDD. In order to distinguish between the two HDD options the following phrases (and their case variants) were searched:

500 GB: 500GB, 500 GB

One TB: 1 TB., 1TB, One TB

Xbox Live (Xbl) is an online service that lets users connect and interact with other Xbox users and download digital content. Using this platform, users can message, talk, and play multiplayer games with others. The platform also contains a considerable amount of digital content that users can download. Two versions of Xbl are offered: a free version and a subscription version. Trial subscriptions of the paid (Gold) version are often included with special edition models. To identify the Xbox listings with Xbox Live subscriptions the following terms (and their case variants) were used:

Live, Xbl, Xbox live, Xbox Lv, Xbox Lve

Next, the listings that included the Kinect sensor (Kinect) were tagged. Kinect is a motion controller with a webcam and voice recognition capabilities that allows Xbox users to control their console (see Figure 8). The listings that included the Kinect sensor were distinguished from those that did not by searching the listing titles for the following phrases (and their case variants):

> *& camera, & kinect, + camera, + kinect, kinect included, kinect not included, w/ camera, w/kinect, w/ kinect, w/o kinect, with camera, with out kinect, with-kinect, without kinect, without-kinect*

The same phrases with misspellings of Kinect, including, "c*onnect*" and "*konect*" were also searched for and used to tag models that included the sensor.

Figure 8: Image of the Kinect sensor

Special Editions

Specific "special edition" Xbox models were identified through a combination of text analytics and manual search (see table 22). These products were essentially manufactured-designated bundles that included either a standard (500 GB) Xbox One console or a console with an upgraded (1 TB) hard drive capacity and at least one game

or accessory. These special edition models were sold as a means of promoting upcoming games that Microsoft expected to be popular. Most of the bundled games are the newest within a previously successful series. For example, the “Halo Guardians” model contained the most recent installment of the Halo series, the most successful series in the entire Xbox lineup, and the game turned out to be the most successful within the series. (Kain, 2015).

An “I made this” special edition, which was given to the employees at the Xbox One manufacturing facility, was also discovered; however, none of those listings resulted in a sale. “Juggernog” and “Batman Arkham Knight” special edition models were also found; however, both models were eventually cancelled and never released to the public. Listings of those two models were removed from the sample.

A “Triple Black” version of the QC25 headphones was also discovered during the product identification process. The Triple Black edition was subsequently tagged as the “Bose Custom” model along with any other deviations from the standard black and white colors.

Table 22: Special Edition Identifiers and Frequencies

Special Edition	Abbreviation	MPN	Freq.	% Xbox	% Total
Assassin's Creed Unity	Assassin's Creed	5C7-00042	912	21.61%	9.01%
Call of Duty: Advanced Warfare	COD: AW	5C7-00075	81	1.92%	0.80%
Day One	Day One	7UV-0005	40	0.95%	0.40%
Elite	Elite	TM3-00002	25	0.59%	0.25%
Fallout 4	Fallout 4	KG4-00026	20	0.47%	0.20%
EA Sports Fifa 16	Fifa 16	KF7-00043	59	1.40%	0.58%
Forza Motorsport 6	Forza 6	KF6-00053	191	4.53%	1.89%
Gears of War: Ultimate Edition	Gears of War	5C5-00081	342	8.10%	3.38%
Halo 5: Guardians	Halo Guardians	KF6-00058	98	2.32%	0.97%
The LEGO Movie Videogame	Lego Movie	5C7-00143	29	0.69%	0.29%
EA Sports Madden NFL 2016	Madden NFL 2016	KF6-00064	267	6.33%	2.64%
Halo the Master Chief Collection	Master Chief	5C6-00017	1,218	28.86%	12.04%
Sunset Overdrive	Sunset Overdrive	6QZ-00026	12	0.28%	0.12%
Rise of the Tomb Raider	Tomb Raider	KF7-00044	14	0.33%	0.14%

Table 23 lists the contents of each special edition model included in the analysis, and figure 9 displays their images. Game(s) were the most commonly paired items, and at least one game appears in every model, other than the "Elite" special edition, which includes an upgraded console with a 1 TB solid state hybrid drive (SSD) and an "Elite" controller with multiple accessories. As shown in figure 9, the COD:AW, Elite, Forza 6, and Halo Guardians editions feature custom colors (skins) for the console and controller that generally reflect the game that is included in the special edition.

Note that some conditions must hold for the product to be considered the manufacturer designated bundle. For example, all Day One Special Edition models should include Kinect (unless "*without kinect*" or "*console only*" was specified in the listing title) and eight of the fourteen special editions should include a 1 TB HDD. The Master Chief special edition was released with and without the 1 TB HDD; however only .05% (6) of the observed listings indicate the presence of the upgraded hard drive. Unless otherwise noted through the listing title (e.g. "*no game"*), all of the standard and bundled contents are assumed to be included in the special edition listings.

Table 24 lists the specific games included in each model and two measures of popularity: the Metascore and User Score from Metacritic.com. These variables are not included in the analysis, but could be added to future research.

Table 23: Contents of Special Edition Xbox One Models

Special Edition	HDD Capacity	Kinect	Color	Headset	Games	Additional Accessories
Assassin's Creed	500 GB	Yes/No	Black	Yes	2,3	Model with Kinect also included Dance Central Spotlight
COD: AW	1 TB	No	Black, Silver, Gold	Yes	1	None
Day One	500 GB	Yes	Black	Yes	0	Commemorative controller, premium packaging, and DLC
Elite	1 TB SSHD	No	Black, Silver	Yes	0	"Elite" wireless controller and 14-day trial of Xbl
Fallout 4	1 TB	No	Black	Yes	2	14-day trial of Xbl
Fifa 16	1 TB	No	Black	Yes	1	DLC and one year of EA Access
Forza 6	1 TB	No	Blue	Yes	1	DLC and 14-day trial of Xbl
Gears of War	500 GB	No	Black/White	No	1	DLC and 14-day trial of Xbl
Halo Guardians	1 TB	No	Silver, Gray, Teal	Yes	5	Spartan themed steel book, DLC, and 14-day trial of Xbl
Lego Movie	500 GB	No	Black	No	1	14-day trial of Xbl
Madden NFL 2016	1 TB	No	Black	Yes	1	DLC and one year of EA Access
Master Chief	500 GB,1 TB	Yes/No	Black/White	Yes	5	14-day trial of Xbl
Sunset Overdrive	500 GB	No	White	Yes	1	Day One DLC and 14-day trial of Xbl
Tomb Raider	1 TB	No	Black	No	2	None

Figure 9: Images of Special Edition Xbox One models

Assassin's Creed

COD: AW

Day One

Elite

Fallout 4

Fifa 16

Forza 6

Gears of War

Halo Guardians

Lego Movie

Madden NFL 2016

Master Chief – White

Master Chief - Black

Sunset Overdrive

Tomb Raider

Note: The Master Chief edition was released in both black and white. The white model was offered with and without Kinect. The Gears of War edition also came in both black and white; however, neither model came with Kinect, and they were identical beyond color.

Table 24: Package Contents and Ratings for Special Edition Models

Special Edition	Game(s) Included	Game Genre[2]	Game Publisher[2]	Metascore[2]	User Score[2]
Assassin's Creed	Assassin's Creed Unity and Assassin's Creed IV: Black Flag (DD)	Action-adventure	Ubisoft	72	4.1
COD: AW	Call of Duty: Advanced Warfare (DD)	Shooter	Activision	81	5.5
Day One	None	NA	NA	NA	NA
Elite	None	NA	NA	NA	NA
Fallout 4	Fallout 4 (PD) and Fallout 3 DD)	Role-playing	Bethesda Softworks	88	6.4
Fifa 16	Fifa 16 (DD)	Sports	Electronic Arts	84	4.4
Forza 6	Forza Motorsport 6 (DD)	Racing	Microsoft Studios	87	7.7
Gears of War	Gears of War: Ultimate Edition (DD)	Shooter	Microsoft Studios	82	7.6
Halo Guardians	Halo 5: Guardians (DD)	Shooter	Microsoft Studios	84	6.5
Lego Movie	The LEGO Movie Video Game (PD)	Action-adventure	Warner Bros. Interactive	69	6.9
Madden NFL 2016	Madden NFL 16 (DD)	Sports	Electronic Arts	84	6.0
Master Chief	Halo: The Master Chief Collection (5 DD games in total)	Shooter	Microsoft Studios	85	7.4
Sunset Overdrive	Sunset Overdrive (DD)	Shooter	Microsoft Studios	81	7.8
Tomb Raider	Rise of the Tomb Raider and Tomb Raider: Definitive Edition (DD)	Action-adventure	Microsoft Studios	86	8.0

Bundles

The complementary nature of the products in the sample promotes the inclusion of accessories. For example, the value of the Xbox entertainment system increases with the addition of games that can be played on it, and the GoPro action camera becomes more useful and valuable as additional accessories and attachments are added. Similarly, the Bose headphones benefit from additional cases and inserts that make it more easily transportable or allow the user to alter its appearance.

The product listings in the sample reveal that the Xbox One is commonly paired with popular games, extra controllers, the Kinect sensor, and headsets; the GoPro is often paired with cases, adapters, and extensions; and the Bose headphones are often bundled with cases, bags, and inserts. To account for these deviations from the standard product, the listing titles were manually read and the following list of terms (extended phrases) was created:

128 gb
128gb
16 gb
16gb
256 gb
256gb
2xs
32 gb
32gb
3-way grip
4 gb
4gb
64 gb
64gb
8 gb
8gb
adapters
advanced
package
all inclusive
arm
bac pac
bacpac
bag
bag pack
band
battery
bobber
cards
carrying bag
case
chair
chest wrist straps
chesty
controler
controller
cyclist/biker
package
DJI Phantom
extendable pole
extra (battery)
extras
flash
gamepad
game(s)
gb sd
gift card
go pole
gooseneck
gooseneck
gopole
grip
handler

head (strap	*moto (edition)*	*sji phantom*
kit	*music (edition)*	*ski bike (kit)*
lens caps	*package*	*smart remote*
many extras	*pet package*	*strap*
memory card	*plus*	*stick*
memory stick	*pole*	*suction (cup*
mic	*ready for adventure*	*surf (edition)*
microphone	*sandisk*	*tripod (mount)*
microsd(xc)	*sd card*	*turtle beach*
more	*selphie stick*	*usb card*
mount	*session bundle*	*water (kit)*

Listing titles with the terms "*acc's, accesories, accessories, accessory, accs accessories, bundle"* were also tagged and manually checked. In most cases these terms indicated that all the standard accessories were included. Unless otherwise specified in the listing title, each listing was assumed to include all the standard accessories and components.

While researching the product identifiers for each of the base products, several manufacturer-designated bundles were discovered. These include the GoPro Black/Silver "Music Edition", GoPro Black/Silver "Moto Edition", GoPro Black/Silver "Moto Edition", and the "GoPro Silver "Surf Edition", among others. Since these bundles were designated by the manufacturer, they can be identified by their MPN (see Table 25) and their contents should be consistent. The listing titles were searched for these MPN and the bundles were tagged accordingly.

The most common bundle involving the GoPro camera is the Music bundle (221 observations), followed by the Moto bundle (208 observations), and the Surf bundle (78 observations). See Figure 10 for images of each. All three bundles are considerably

more expensive than the standard GoPro package ($369.91), with average prices of $483.73, $414.90, and $429.96, respectively.

Table 25: GoPro-Designated Bundle Identifiers

Special Edition or Bundle	MPN
GoPro Black - Music bundle	CHDBX-401
GoPro Black - Moto bundle	CHDMX-401
GoPro Black - Surf bundle	CHDSX-401
GoPro Silver - Music bundle	CHDBY-401
GoPro Silver - Moto bundle	CHDMY-401
GoPro Silver - Surf bundle	CHDSY-401
GoPro Session - French edition	CHDHS-101-EU
GoPro Black - French edition	CHDHX-401-EU
GoPro Black - German edition	CHDHX-401-DE
GoPro Black - French Moto bundle	CHDMX-401-EU
GoPro Black - French Music bundle	CHDBX-401-EU
GoPro Hero 3+ Black	CHDHX-302

All the GoPro bundles listed in table 25 were removed from the sample, either because the titles indicated considerable variation in the bundle contents, they had foreign specifications, or because they were not in the GoPro Hero4 line of products. The addition of these bundled listings is left to future research.

.

Figure 10: Images of the Most Popular GoPro Bundles

GoPro Silver Moto Bundle

GoPro Silver Surf Bundle

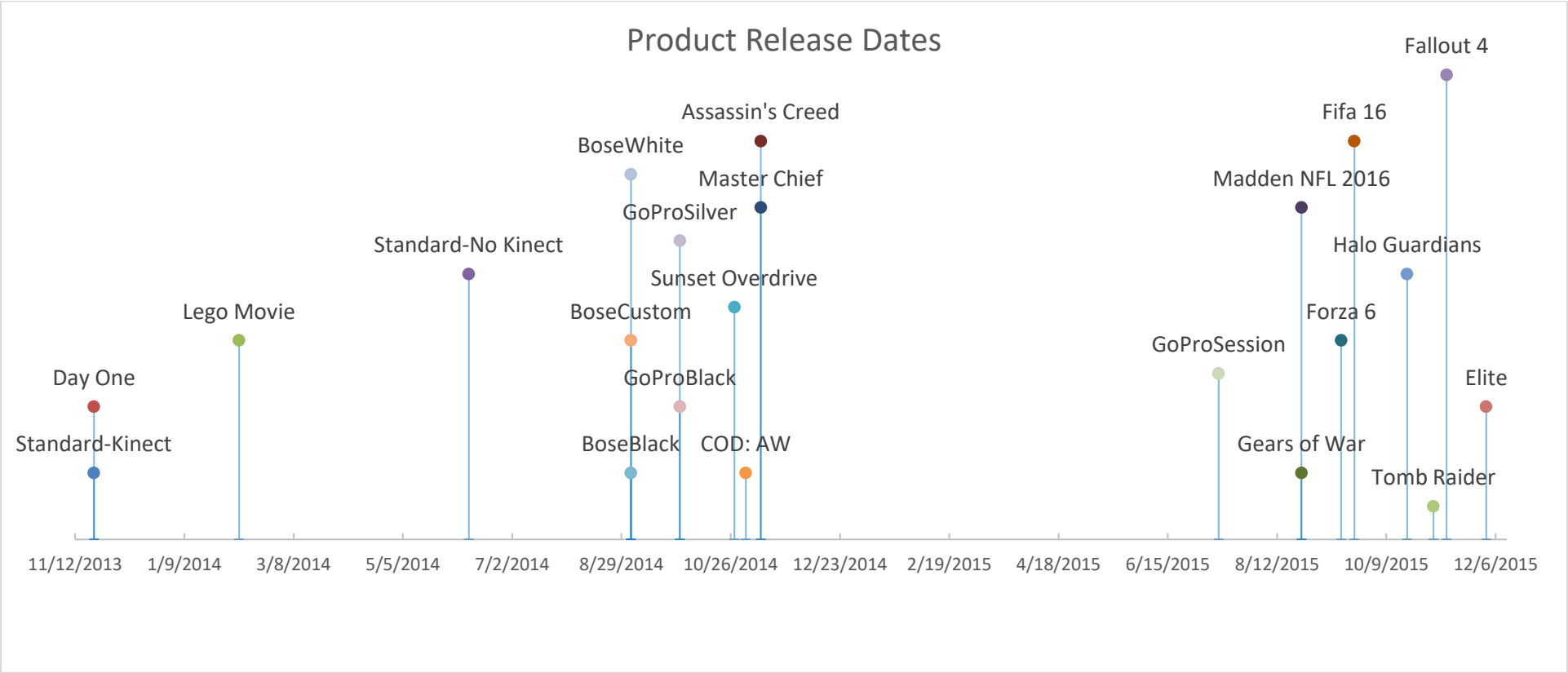
GoPro Silver Music Bundle

Many other bundles were found during the manual search of listing titles, including some additional manufacturer-designated bundles. However, the names and contents of these bundles were also found to vary considerably despite the manufacturer's designation. These other bundles were also substantially larger than the three presented on the previous page. The "*Ultimate Accessory Package (128GB)*" bundle, for example, contains over 20 accessories. Other GoPro bundles (not listed in table 25) include the *Advanced Accessory Package (32GB), Advanced Kit, All Inclusive Bundle, Cyclist/Biker Package, DRP Custom Bundle, Extreme Bundle, Intermediate Bundle (64GB), Must Have Accessories Package (16GB), Pet kit, Professional Accessory Package (32GB), Professional Accessory Package (64GB), Ready for Adventure Kit, Starter Kit, Ultimate Accessory Package (128GB), Ultimate Kit, Water Ski Bike Kit*. Since the descriptions for these bundles varied widely and a standard list of contents could not be obtained, these other bundles were removed from the sample. The identification of these other bundles is left for future research.

Product Release Dates

Figure 11 displays the release dates for each product. Note that the height of the bars has no meaning and varies to make the labels more legible. Clearly, the products included in the listings were not released simultaneously, and the timing within the various product lifecycles could account for some of the variation in the landed price and time to sale. In fact, except for the Bose QC25 headphones, which were all released on September 3, 2014, the products are observed at dramatically different stages of their product lifecycles. This is accounted for with the variable *Weeks from Launch* that is a count measure of the weeks between the product release and the time of sale.

Figure 11: Product Release Timeline



Preorders

Some preorder sales (sales occurring prior to product launch) exist in the sample. In fact, all Elite special edition sales were presales, because the product launch date (12/01/2015) is after the latest script execution date (11/18/2015). The listing titles (see table 26) confirm that these were in fact presales and not errors in data collection. Overall, 82 presale observations were tagged, which is less than 1% of the sample. The *Weeks from Launch* values for all presales was coded as zero.

All presales of models that were eventually released to the public were included in the analysis; however, sales of special editions that were eventually cancelled prior to release were removed from the sample. Thus, the "Juggernog" and "Batman Arkham Knight" special edition Xbox models were removed.

Table 26: Example Listing Titles of Preorders

Product	Listing Date	Product Launch	Example Preorder Listing Title
Forza 6	7/20/2015	9/15/2015	Xbox One Console Forza Motorsport 6 Limited Edition 1TB - Ships on Release Date
Forza 6	6/30/2015	9/15/2015	Xbox One Forza 6 Limited Edition 1TB Bundle PREORDER oneqvoDOTcom
Forza 6	9/1/2015	9/15/2015	Xbox One Forza 6 Limited Edition 1TB Bundle PreOrder
Forza 6	9/7/2015	9/15/2015	XBOX ONE FORZA 6 LIMITED EDITION 1 TB BUNDLE BY MICROSOFT ~ PREORDER 9/15/15~
Forza 6	8/30/2015	9/15/2015	New Xbox One Forza 6 Limited Edition Bundle 1tb Console Microsoft Ships 9/15
Forza 6	9/3/2015	9/15/2015	Microsoft Forza XBox One Videogame Console System Bundle Blue 1TB NEW PREORDER
Forza 6	8/25/2015	9/15/2015	Xbox One Console Forza Motorsport 6 Limited Edition 1TB - PRE ORDER
Halo Guardians	9/21/2015	10/20/2015	Xbox One Console Halo 5: Guradians Limited Edition 1TB - Ships on Oct 20
Halo Guardians	9/26/2015	10/20/2015	Xbox One Console Halo 5: Guradians Limited Edition 1TB, NEW - Pre-ORDER 10/20/15
Halo Guardians	9/17/2015	10/20/2015	Xbox One Console Halo 5: Guradians Limited Edition 1TB, NEW - Pre-ORDER!
Halo Guardians	9/9/2015	10/20/2015	Xbox One Console Halo 5: Guradians Limited Edition 1TB - Ships on Release Date
Gears of War	7/15/2015	8/25/20105	PREORDER Xbox One Gears of War: Ultimate Edition 500GB Bundle
Gears of War	8/6/2015	8/25/20105	Xbox One Gears of War: Ultimate Edition 500GB Bundle Preorder 8/25/15
Elite	11/7/2015	12/1/2015	Xbox One 1TB Elite Console Bundle ~ BRAND NEW - FREE SHIPPING ~ PREORDER 12/1/15
Elite	11/16/2015	12/1/2015	New Xbox One Elite Bundle Black 1TB Console Bundle Pre-order **Ships 12/01**
Elite	10/7/2015	12/1/2015	Microsoft Xbox one 1 TB elite Console (Black) Pre-Sale
Elite	11/10/2015	12/1/2015	Xbox One Elite Console 1TB Bundle - Ships on Dec 1- Below Retail Price
Elite	11/1/2015	12/1/2015	Xbox One 1TB Elite Console Bundle-Pre order
Fallout 4	10/17/2015	11/10/2015	Xbox One Console 1TB Fallout 4 Bundle - Ships on Nov 10

Note: All the “Elite” listings were preorders.

Final Identification Checks

A second round of manual product identification was conducted between 4/1/2018 and 4/14/2018. The listings were sorted by product and manually verified by their titles. This second reading confirmed the accuracy of the previous product identification procedures and ensured the accuracy of the data cleaning conducted since that initial round. Keyword search was used to supplement manual identification.

Trimming Procedures

In a final effort to account for extreme outliers, the dependent variables (*Landed Price* and *Hours to Sale*) were trimmed at various thresholds. Small cutoff values were used to avoid overfitting the data. The 5% level is used in the base models and 1%, 2%, and 10% are reserved for robustness checks.

Figure 12: Original and Trimmed Landed Price

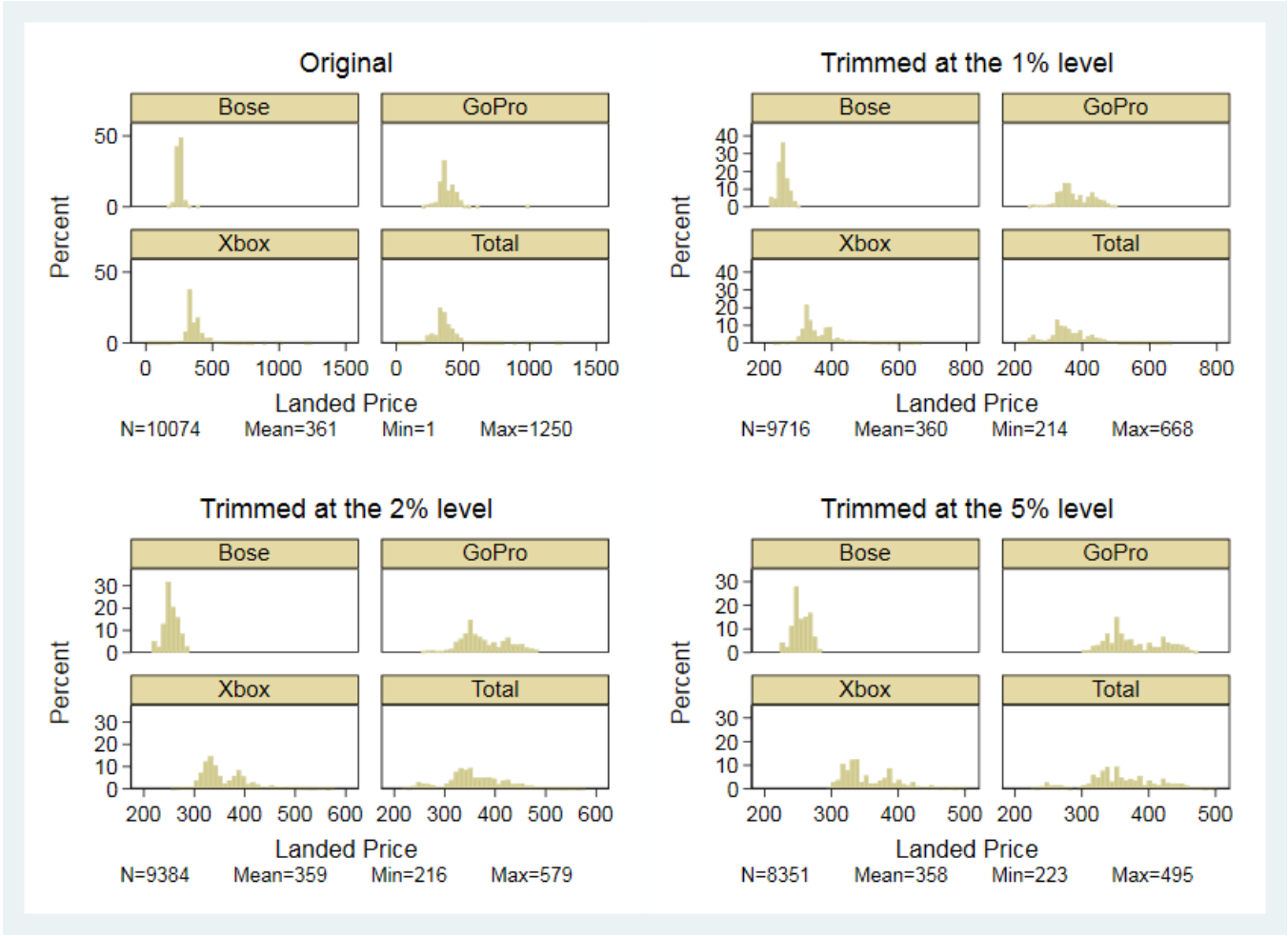
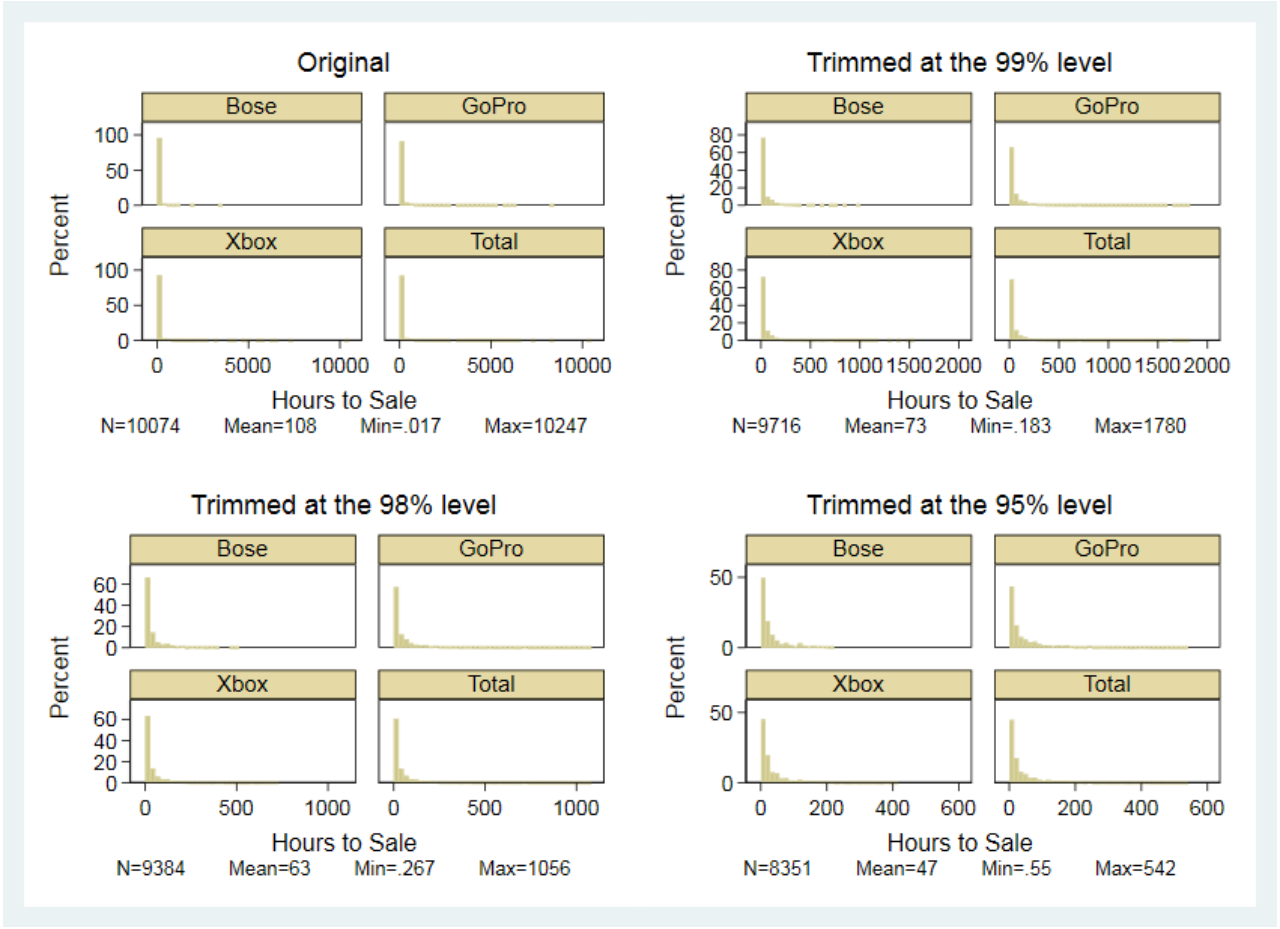


Figure 13: Original and Trimmed Hours to Sale



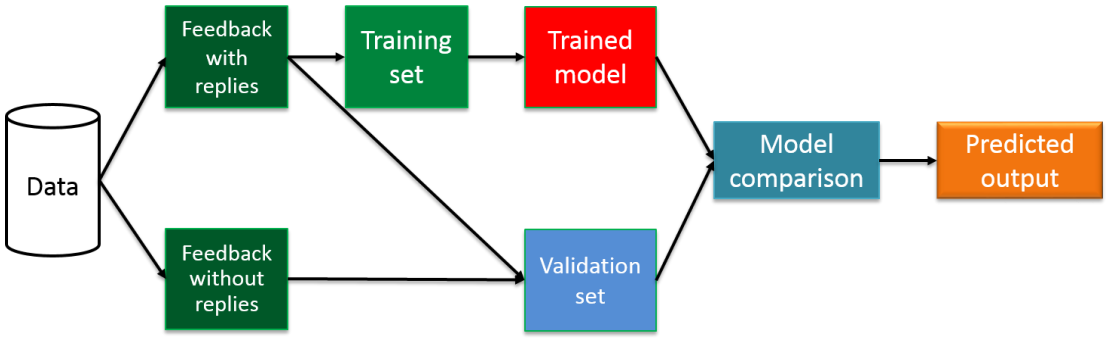
Appendix C: Feedback Classification

OVERVIEW

Essay 2 uses content analysis and text analytics to create variables from sellers' feedback histories. The conventional text-classification procedures using the vector-space approach are used (Salton, 1971, 1989). An extensive tagging process and correlation coefficients, relating term prevalence to tag categories, are used to train a predictive model of the transaction outcome, satisfaction of the buyer, and complaint type. Then, the model is applied to large set of feedback posts to create measures of seller reputation based on buyer feedback. Finally, these measures are regressed against the time to sale for the sellers' current listings to estimate the impact of feedback text on demand.

Literature-based procedures are used to train the model (Ng et al., 1997; Fan et al., 2005; Coussement and Van den Poel, 2008; Abrahams et al., 2012, 2014). The process is depicted in Figure 14 and summarized below.

Figure 14: Depiction of Tagging Methodology



First, the entire feedback history of the sellers was collected from eBay. Next, the posts with replies by the seller and/or follow-up comments from the buyer were separated from those with only a single comment. Since the posts with replies were expected to be more negative than posts without replies or follow-up comments, a random sample of 5,000 was selected from this subset to train the model. Another random sample of 2,500 was selected from the full sample for validation purposes.

Next, with the aid of faculty, PhD students, and MS students from the Supply Chain Management and Business Analytics departments at three American Universities, a tagging protocol was developed. A trial tagging run was then conducted on 200 randomly drawn feedback posts with replies, prompting minor revisions to the tagging protocol.

Through an online interface called PamTag[4], human taggers categorized 5,000 feedback thread based on the transaction satisfaction of the buyer, complaint type, and transaction outcome. After the entire sample was tagged and sufficient interrater reliability had been achieved, correlation coefficients (Ng et al., 1997, Fan et al., 2012) were used to determine the words indicative of each category of complaint type, outcome, and satisfaction. A category-specific dictionary was created for each

[4] http://vtip.technologypublisher.com/technology/20936

category, and each term within the dictionaries was assigned a prediction weight (prevalence score). Then, the dictionaries were applied to 2,500 randomly drawn threads, and the prevalence scores of all matched terms were summed and used to classify the threads within the categories. These predicted outcomes were then verified against an additional round of human tagging and performance measures were evaluated. The now validated category-specific dictionaries were applied to all remaining feedback threads and the results were grouped by seller. Finally, the predicted seller-level measures were tied to the listings data to quantify the impact of various types of feedback text on sellers' landed price and time to sale.

DATA CODING

As previously mentioned, a training set was assembled to classify feedback into the following categories: *transaction outcome, transaction satisfaction,* and *complaint type*. Prior to tagging, all buyer and seller IDs were replaced with generic terms (i.e. Buyer, Seller) and the date and time of follow-up comments were removed.

Next, a tagging protocol, with detailed instructions on how to tag each feedback post, including definitions of each tag type and example tags, was produced and verified in a trial study. This tagging protocol, which is presented in Ap. D, includes a mutually exclusive and collectively exhaustive list of possibilities, which are summarized below.

Transaction Outcome

This category describes the end result of the transaction. There are seven possible

outcomes of a transaction on eBay: the product could be retained, returned, or exchanged, the product could be lost in the delivery process, the buyer or seller could cancel the transaction prior to delivery, or the seller could issue a refund post-delivery. The taggers were asked to identify the most specific and accurate outcome achieved during the transaction. Therefore, if a buyer indicated that a refund was issued, and complains about having to pay the return shipping, then the Returned transaction outcome is tagged. Similarly, if a product was never received, because the seller reneged on the transaction, then a Seller Cancellation transaction outcome is tagged. If the outcome is unclear, then the most conservative outcome, Retained, is assumed.

Since sellers can reply to buyer comments and offer inaccurate counter-information, the taggers were asked to identify the outcome from the buyer's comments only (unless seller information was verified in follow-up comments from the buyer). For example, the following outcome was identified as Refunded, with a Negative satisfaction and Misrepresentation complaint, from the buyer's comments, despite the seller's claim that the item was never received:

> *Feedback from the buyer: Very bad experience, item far from description. eBay support have to issu refund ----- Reply by the seller: Cust sent back sig req mail. some people have jobs post office closes 5pm.*

Transaction Satisfaction

The satisfaction rating (positive, neutral, negative) associated with a feedback post on eBay is not immediately available in our dataset; however, this information can be gleaned from the feedback text. Taggers were asked to interpret the entire thread,

including follow-up comments, and decide whether the overall feedback from the buyer is positive, neutral, or negative. Therefore, the *Transaction Satisfaction* describes the buyer's overall satisfaction at the end of the thread. Thus, the situation where a buyer initially describes an issue that arose during the transaction, gives the seller a negative rating, and then praises the seller in a follow-up comment, is tagged as Positive satisfaction. This approach accounts for premature feedback ratings and is more accurate representation of the overall buyer satisfaction than the initial numerical rating in isolation.

This process of human interpretation mimics the process that every eBay buyer goes through when they view an online seller's feedback profile prior to making a purchase. This method avoids incorrectly rated posts, such as when a buyer accidentally gives a good seller a negative rating and then indicates their mistake in a follow-up post (e.g. "Follow-up by the buyer: I was wrong... Wish I could change feedback to positive! Item WAS listed used."). This method also correctly identifies the situation when a buyer prematurely leaves positive feedback and then subsequently detects a problem with the transaction (e.g. "Follow-up by the buyer: Should of waited b4 leaving feedback stereo plays CDs w/ lots of static. N shipped poor.").

Complaint Type

This category is used to identify the object of the buyer's complaint, if any. Complaints could be on the seller's process for handling returns or issuing refunds, the seller's communication, the delivery of the product, or the product's description, price,

or quality. Complaints could also indicate that the seller reneged on the transaction or sold an illegal/counterfeit item.

Multiple complaint types could be assigned to each post. For example, communication complaints often accompany complaints about sellers' return/refund management and misrepresentation complaints are frequently paired with complaints about quality. Please see the Tagging Protocol in Appendix D for a complete description of each complaint type category and several examples.

Service Recovery

One additional category, *Service Recovery*, was created from the combination of transaction satisfaction and complaint type. A service recovery was deemed to take place if the feedback thread has at least one complaint and the transaction satisfaction is positive or neutral. This captures the situation where the buyer initially left a negative comment (and likely a negative rating, although this is not recorded) and then revised their opinion of the seller after a service recovery. For example, in the following thread the buyer initially makes a Misrepresentation complaint and then follows up by complementing the sellers' successful service recovery:

> *"Feedback from the buyer: It was 3/8 not 1/4 and screws in block broke off. Could not put on new handle ----- Follow-up by the buyer: They took care of problem, give them 4 star."*

The above is considered a service recovery, because the buyer states that the seller corrected an issue (Misrepresentation) and recommends a Positive seller rating (4 out of 5 stars).

In many cases involving service recovery, the issue that arose is unclear and the complaint type is Nonspecific, as in the following:

> *Feedback from the buyer: The seller made a honest mistake on their posting, in return gave me a $75.00 return ----- Reply by the seller: Posted wrong pic on my listing. Details were correct but not pic great buyer A+."*

Many service recoveries result in revisions to the buyer feedback, indicated by the phrase "Feedback was revised by the buyer" at the end of the thread. In the following example, the buyer makes a Nonspecific complaint and states that the issue is resolved without praising the seller, resulting in a service recovery with Neutral feedback:

> *Feedback from the buyer: The seller offered to refund my money for the inconvenience presented. ----- Feedback was revised by the buyer.*

Similarly, the following thread involving a Refund includes a Delivery complaint and a successful service recovery, with Positive feedback:

> *Feedback from the buyer: Seller contacted me and worked with me. Received a full refund, USPS lost pkg. Would buy from them again ---- Feedback was revised by the buyer.*

These examples can be contrasted with the following threads, which include a feedback revision but are not considered a service recovery, due to Negative buyer satisfaction:

Feedback from the buyer: The pens work wonderful, but the communication was poor ----- Feedback was revised by the buyer.

Feedback from the buyer: Tho we've fixed issue, I hope seller understands error and fixes problems. ----- Feedback was revised by the buyer.

DATA PROCESSING

A team of eight human taggers classified the 7,500 feedback posts within the training and validation sets, using the tagging protocol in Appendix D. The taggers were seven MS students in the supply chain management program of a major mid-Atlantic University and the lead author. Five of the taggers were female and three were male. Each of the taggers had been living in the US for at least one year prior to joining the team.

For the training set, each member of the tagging team was asked to tag 900 feedback posts over six weeks, and for the validation set, each tagger completed 400 tags over three weeks. In all cases, the posts were randomly selected and there was significant overlap among taggers to test for inter-rater reliability, which is measured using Cohen's Kappa (Cohen, 1960). The degree of agreement amongst the taggers is presented in the next subsection.

Taggers were asked to comment on threads that they were uncertain about using the built-in comments box. Uncertainty could arise from unspecific transaction outcomes, posts in foreign languages, and/or conflicting comments from the buyer.

Short comments in foreign languages (e.g. “Vendedor seguro y fiable 100%;” “lo recimiendo;” “abuso en gastos de envoi”) that were easily translatable using publicly available translators (e.g. Google Translate) were marked and retained if there was agreement across all three tagging categories. Longer foreign posts and foreign posts where the taggers disagreed with respect to at least one tagging category were removed. Posts where all the buyer comments were removed by eBay were also dropped. This process resulted in the removal of 42 unique posts and 61 total tags (0.87%), reducing the training set to 6,942 tags.

Five taggers, including the lead author, tagged the requested 900 posts in the training set, and one tagger tagged an additional four. The other two taggers tagged 715 and 890 posts, respectively. Six null responses were removed, leaving 7,003 total observations. All 5,000 unique posts in the training set were tagged, and approximately three quarters (3,764=75.28%) were tagged by more than one person. The tagging process went faster than expected and was completed in 48 days (2/15/17 to 4/4/17). Six null responses were removed, leaving 7,014 total tags.

Each of the seven taggers completed the 400 requested tags in the validation set, and there was overlap (i.e. more than one tagger) on 297 threads. The taggers agreed on the majority of these overlapping threads, and the remaining were reconciled using a “majority opinion” conflict-resolution strategy or determined by the authority (lead author) when a majority opinion was lacking. After comparing and reconciling tags,

343 duplicate observations were removed from the validation set.

TRAINING SET RESULTS

Feedback Structure

As previously mentioned, the training set is limited to feedback posts with more than one post (either a follow-up comment from the buyer or a reply from the seller). In general, the threads fall into one of two categories: reinforcement or retaliation. Typically, the buyer either praises the seller ("Great seller! A+") and the seller thanks the buyer for their positive comment ("Great Buyer! Thanks for the positive feedback!") or the buyer criticizes the seller ("Horrible seller. Called me an idiot due to a misunderstanding. BEWARE!") and the seller offers a counterargument ("He bought wrong game for his system. I refunded fully.") or makes a complaint of their own ("Unreasonable eBayer. Tried to bully me into breaking return policy.").

In rare cases, the seller may respond to criticism in a helpful way ("Truly apologize for problem, please contact me for 100% satisfaction."), which often leads to a positive follow-up from the buyer ("Standup guy. Payed for unexpected repair with item. VERY Trustworthy"), feedback withdrawal ("Buyer and seller mutually agreed to withdraw feedback for this item.") or feedback revision ("Feedback was revised by the buyer."). Thus, even after receiving a negative rating, the seller can still successfully recover from a service failure, which may impact their perceived trustworthiness in the future. The opposite is also true: sellers that do not resolve the issue often receive follow-up

reinforcement from the buyer, as in “Seller's only response to my emails was to leave negative feedback for me.” This lack of recovery by the seller and reinforcement by the buyer may compound the impact of the buyer’s initial complaint.

Inter-Rater Reliability

Inter-rater agreement is defined as the propensity for two or more individuals to independently classify a given post into the same category. In the present context, inter-rater reliability measures the propensity for the taggers to independently classify (tag) the feedback posts into the same transaction outcome, transaction satisfaction, and complaint type categories.

Table 27 presents the Cohen’s Kappa (**κ**) values of inter-rater reliability (Cohen, 1960) and the strength of agreement categorization from Landis and Koch (1977). Note that the **κ** value for Complaint Type is biased downwards, because multiple complaint types could exist in each post. The **κ** value, in this case, measures the exact agreement with respect to all possible complaint types within each post. The average Cohen’s Kappa across all three fields is 0.662, representing “Substantial” agreement across the eight taggers.

Table 27: Inter-Rater Reliability Measures

Field	Cohen's κ	Strength of Agreement
Training Set		
Transaction Outcome	0.662	Substantial
Transaction Satisfaction	0.766	Substantial
Complaint Type*	0.558	Moderate

* Biased downwards

Descriptive Statistics

Descriptive statistics of the training set are in Table 28. As expected, neutral and negative feedback is much more prevalent than in prior studies: 46.64% versus <1% in Cabral and Hortacsu (2010). As previously mentioned, this is because this sample includes only feedback with replies from the seller or follow-up comments from the buyer, which were expected to include more negative or neutral feedback.

Also, as expected, a moderately high percentage of transactions (17.25%) involved an unexpected outcome; that is, an outcome other than the buyer retaining the product. 3.70% of these unexpected outcomes involved a cancellation, 4.63% involved a non-delivery, and 8.92% involved an exchange, refund, or return. However, due to the relatively low frequency of unexpected outcomes, two aggregate measures were created: *Returned* and *Nonreceipt*. *Returned* is equal to one if the feedback thread indicates that the product was exchanged or returned or if a refund was given. *Nonreceipt* captures outcomes involving a Non-Delivery, Seller Cancellation, or Buyer Cancellation.

Over half (56.30%) of the posts were without a complaint, while 17.81% included multiple complaints. Of these complaints, quality was mentioned the most often, followed by delivery, misrepresentation, and communication. Return/refund complaints, non-specific complaints, price complaints, cancellation complaints, and black-market complaints occurred less frequently. 90% of the complaints are deemed trust-revoking.

Of the 3,060 transactions with at least one complaint, 477 (15.59%) were considered successfully resolved (i.e. the overall thread indicated that the transaction satisfaction was positive or neutral).

Table 28: Summary Statistics on the Training Set Tags (7,003 transactions)

Tagging Category	**%**	**#**
Transaction Outcome		
Buyer cancellation	0.53%	37
Exchanged	0.43%	30
Non-delivery	4.63%	324
Refunded	6.00%	420
Retained	82.75%	5795
Returned	2.50%	175
Seller cancellation	3.17%	222
Transaction Satisfaction		
Positive	53.36%	3737
Neutral	9.58%	671
Negative	37.06%	2595
Number of Complaints		
None	56.30%	3943
Single	25.89%	1813
Multiple	17.81%	1247
Complaint Type		
Return/refund complaints	4.81%	337
Quality complaints	15.46%	1083
Price complaints	2.31%	162
Nonspecific complaints	4.27%	299
Misrepresentation complaints	10.35%	725
Delivery complaints	12.99%	910
Communication complaints	10.35%	725
Cancellation complaints	2.60%	182
Black market complaints	2.06%	144

FEATURE SELECTION

For each of the transaction outcomes, satisfaction levels, and complaint types we develop a list of terms that are significantly more prevalent in the category than in all other subcategories, as measured by the Correlation Coefficient (CC) metric (Ng et al., 1997, Fan et al., 2012). However, prior to this analysis, several pre-processing steps were required, as documented below.

Pre-Processing

In line with the procedures recommended by Ng et al. (1997) and Spangler and Kreulen (2007), the following pre-processing steps were performed prior to the calculation of the CC scores.

1. Reconcile conflicting tags
2. Drop all duplicates
3. Convert all characters to lower case
4. Remove stock phrases
5. Remove all common English prepositions, conjunctions, and auxiliary verbs
6. Pad and then remove all non-alphabetic and foreign language characters
7. Remove excess spaces
8. Convert all words to their morphological roots

Of the threads that were tagged by more than one person, the taggers were in perfect agreement across all categories [transaction outcome, transaction satisfaction, and

complaint type(s)] 59.71% (=2227/3764) of the time. As expected, the complaint type category was the most common form of disagreement, due to the possibility of multiple values for each thread.

The 1,537 tag conflicts were resolved using the majority opinion. If opinions were tied, the authority (lead author's) opinion was used. If a majority was not found and the authority did not tag the post, the lead author manually read the post and made the final decision. Once the tag conflicts were resolved, all duplicate tags were removed from the training set. The remaining pre-processing steps were done automatically using Visual Basic for Applications (VBA) scripts.

In step 4, the standard text (stock phrases) that eBay uses to identify the buyer or seller leaving the comment was removed, because it does not provide additional information on the prevalence of a tagging category. More specifically, the standardized text presented to the taggers (i.e. "Feedback from the buyer:", "Reply by the seller:", and "Follow-up comment from the buyer:") was removed. The value used to separate posts within a thread (-----) was also removed. Other text provided by eBay, such as "feedback was revised by the buyer" and "buyer and seller mutually agreed to withdraw feedback for this item," were not removed, because they may include terms that are indicative of tagging categories.

Using a custom VBA module, prepositions, conjunctions, auxiliary verbs, etc. were removed using the 174 stop words from a publicly available English stop word

dictionary[5]. In addition, three setting-specific symbols: the apostrophe (‘), dash (-), and forward slash (/) were removed to prevent errors in step 7, such as “don’t” => “don t”, “pre-owned” => “pre owned”, and f/b” => “f b”, instead of “fb”, a common abbreviation for “feedback”. The module also converted three symbols ($, #, @) into their word form (money, number, at), since they are commonly used in feedback and may help to identify the tagging category. Numbers (0-9) were also removed. Table 29 includes the full set of stop words removed during this preprocessing step.

[5] xpo6.com/list-of-english-stop-words/

Table 29: Stop Words Removed During Pre-Processing

Words	by	having	it	out	these	what's	**Numbers**
a	can't	he	it's	over	they	when	0
about	cannot	he'd	its	own	they'd	when's	1
above	could	he'll	itself	same	they'll	where	2
after	couldn't	he's	let's	shan't	they're	where's	3
again	did	her	me	she	they've	which	4
against	didn't	here	more	she'd	this	while	5
all	do	here's	most	she'll	those	who	6
am	does	hers	mustn't	she's	through	who's	7
an	doesn't	herself	my	should	to	whom	8
and	doing	him	myself	shouldn't	too	why	9
any	don't	himself	no	so	under	why's	**Punctuation**
are	down	his	nor	some	until	with	/
aren't	during	how	not	such	up	won't	-
as	each	how's	of	than	very	would	'
at	few	i	off	that	was	wouldn't	**Symbols**
be	for	i'd	on	that's	wasn't	you	$
because	from	i'll	once	the	we	you'd	#
been	further	i'm	only	their	we'd	you'll	@
before	had	i've	or	theirs	we'll	you're	
being	hadn't	if	other	them	we're	you've	
below	has	in	ought	themselves	we've	your	
between	hasn't	into	our	then	were	yours	
both	have	is	ours	there	weren't	yourself	
but	haven't	isn't	ourselves	there's	what	yourselves	

Note: Punctuation was converted to blanks and symbols were converted to words; all other terms were replaced with a single space.

Two VBA modules were then used to remove foreign language symbols and then pad (i.e. add a space in place of) and remove all remaining nonalphabetical characters. Padding corrected punctuation errors that would of otherwise resulted in concatenated strings (e.g. Really,really => Reallyreally). Excess blank spaces were also removed at this time.

Finally, each word was converted to its morphological root using the WordNet Lemmatizer from Miller (1990). For example, malignant, malfunction, and malice could be reduced to their root form “mal”, meaning bad; while, reject, recede, return, revert, and redeem could be reduced to “re”, meaning back or again. This process of “text compression” converts words into a form that is better adapted to computer manipulation and greatly improves processing speed and classification accuracy (Salton, 1989). Words with equal meaning (synonyms) are also removed, reducing the relevant word set considerably without any loss of text content.

The pre- and post-processing examples in table 30 demonstrates the impact of the transformation. Note that the tagged categories are also listed at the bottom of the table for reference purposes. The first line in the table presents the original feedback as presented to the taggers. The second line presents the lowercase version without the stock phrases (e.g. Feedback from the buyer:). Stop words (e.g. I, had, to, this, of, $, 1-9, was, -) were removed in Step 5, and all non-alphabetical and foreign languages characters were removed in Step 6. Step 7 removed excess spaces, and in the final step, the words were converted to their morphological roots, leaving the fully transformed version, which was used to calculate the CC scores.

Table 30: Pre-Processing Example

Original:	Feedback from the buyer: I had to return this hunk of junk.Disappointing wasted $13 to return it! ----- Reply by the seller: Mr. Crazee was offered eBay Hassle-Free return label, refused to use it. Avoid.
Steps 3,4:	i had to return this hunk of junk.disappointing wasted $13 to return it! mr. crazee was offered ebay hassle-free return label, refused to use it. avoid.
Step 5:	return hunk junk.disappointing wasted money return it! mr. crazee offered ebay hasslefree return label, refused use it. avoid.
Step 6:	return hunk junk disappointing wasted money return it mr crazee offered ebay hasslefree return label refused use it avoid
Step 7:	return hunk junk disappointing wasted money return it mr crazee offered ebay hasslefree return label refused use it avoid
Transformed:	return hunk junk disappoint wast money return it mr craze offer ebay hasslefre return label refus use it avoid
Satisfaction:	Negative
Outcome:	Returned
Complaints:	Return/Refund Complaint, Quality Complaint

Word counts for each thread were also recorded at this time to normalize posts based on their length. Within the processed feedback threads, there were a total of 3,729,996 "words" (stems). The average length of a thread was between six and seven words, with a minimum of one and a maximum of 540. There were 4,247 unique words (unigrams), 26,906 unique two-word phrases (bigrams), and 36,904 unique three-word phrases (trigrams).

Category-Specific Dictionaries

Forty-eight dictionaries were produced through the analysis of CC scores. Three scoring units (unigram, bigram, trigram) were used and sixteen categories (three transaction outcomes, three satisfaction levels, and ten complaint types) were

considered. Each category- and scoring unit-specific dictionary is comprised of a list of features (words or phrases) and weights (prevalence scores) that reflect the prediction quality of the feature. The highest weights are given to the features that exhibit the highest frequency of presence within the category. Scores of zero indicate that the feature offers no informational value, and therefore, only features with positive scores are useful for category prediction. The dictionaries were then sorted alphabetically and later by prevalence score for evaluation. Irrelevant terms, such as seller usernames and concatenated words, were manually removed at the discretion of the lead author.

Table 31 presents the 25 word-stems (unigrams) most prevalent in each transaction outcome and satisfaction category, and tables 32 and 33 present the 25 words most prevalent in the complaint type categories. The prevalence (CC scores) are reported in parentheses. The bigram (two-word) and trigram (three-word) dictionaries are presented in tables 34-36 and 37-40, respectively. The prediction performance of each is assessed in the next section.

Table 31: Top 25 Words (Prevalence Scores) by Outcome and Satisfaction

	Transaction Outcome			Transaction Satisfaction		
	Retained	**Returned**	**Nonreceipt**	**Positive**	**Neutral**	**Negative**
1	thank (32529)	refund (44332)	slow (26668)	thank (97272)	revis (12510)	refund (54376)
2	great (27801)	full (19817)	ship (26642)	great (77597)	feedback (11434)	never (46711)
3	fast (19862)	money (13530)	never (26414)	fast (55150)	littl (10970)	item (46286)
4	a (16782)	gave (13327)	receiv (26291)	a (53577)	neutral (10052)	bad (36124)
5	busi (15336)	mistak (11927)	usp (24069)	busi (42059)	bit (9399)	money (35447)
6	high (14297)	given (9617)	took (23171)	high (39237)	ok (9180)	sent (35087)
7	recommend (13808)	partial (9230)	item (22701)	you (37729)	though (8554)	bewar (34569)
8	good (13550)	offer (8924)	track (21749)	recommend (36247)	okay (8044)	return (33947)
9	you (12498)	immedi (7907)	paid (21598)	enjoy (32725)	appolog (7660)	contact (33728)
10	enjoy (11182)	issu (7391)	sent (21153)	excel (32598)	learn (6334)	full (30284)
11	gt (11071)	sent (7049)	delay (20382)	gt (29950)	parti (6254)	email (29569)
12	describ (10630)	fulli (6875)	packag (19408)	lt (29625)	comment (5664)	list (28163)
13	lt (10430)	item (6788)	mail (19215)	revis (28290)	slow (5613)	offer (28008)
14	excel (9977)	half (6730)	time (18648)	transact (27887)	hat (5560)	sold (27774)
15	glad (8946)	wire (6675)	still (18509)	awesom (25746)	pad (5560)	refus (27466)
16	awesom (8696)	return (6670)	late (17730)	glad (24568)	buyer (5555)	want (26859)
17	much (8635)	replac (6460)	wrong (17076)	again (24520)	user (4907)	use (26357)
18	posit (7974)	india (6430)	week (16609)	pleasur (24348)	famili (4904)	get (26223)
19	pleasur (7845)	threw (6430)	reciev (16319)	much (24103)	paint (4904)	day (25689)
20	u (7532)	encount (6430)	deliv (16181)	good (23884)	slight (4904)	damag (25469)
21	welcom (7412)	relat (6430)	up (16030)	quick (23122)	canada (4904)	paid (25326)
22	super (7191)	still (6273)	poor (15749)	u (21683)	resolv (4885)	said (24823)
23	hope (7123)	bad (5926)	long (15447)	posit (21163)	paid (4879)	tri (24514)
24	again (7070)	lie (5680)	get (14953)	hope (21154)	cmon (4865)	cancel (24327)
25	perfect (6897)	got (5517)	wait (14887)	welcom (20952)	besid (4865)	broken (24275)

Table 32: Top 25 Words (Prevalence Scores) by Complaint Type (Group I)

	Black Market	**Cancellation**	**Communication**	**Delivery**	**Misrepresentation**
1	fake (18293)	cancel (29713)	email (32829)	day (29713)	descript (29580)
2	stolen (17221)	stock (15093)	respond (22254)	slow (26668)	new (23494)
3	bootleg (8437)	higher (13292)	rude (21630)	ship (26642)	list (23148)
4	counterfeit (8437)	won (11544)	repli (19882)	never (26414)	use (22855)
5	authent (8223)	explan (10647)	communic (19281)	receiv (26291)	lie (16612)
6	sell (7880)	relist (10639)	messag (17959)	usp (24069)	state (16309)
7	sold (6751)	refund (10010)	answer (17594)	took (23171)	pictur (15205)
8	blacklist (6703)	immedi (8141)	never (16921)	item (22701)	said (15200)
9	assur (6703)	inventori (8114)	poor (15891)	track (21749)	read (14389)
10	brick (6703)	order (7870)	bad (15308)	paid (21598)	mention (13763)
11	real (5887)	item (7626)	respons (14719)	sent (21153)	pic (13532)
12	author (5684)	auction (7447)	refund (13147)	delay (20382)	size (13370)
13	verizon (5684)	want (6792)	seller (12712)	packag (19408)	item (13033)
14	fraud (5540)	accid (6784)	liar (12355)	mail (19215)	scratch (12962)
15	thief (5509)	hurt (6624)	sent (12238)	time (18648)	describ (12945)
16	stori (5415)	miscommun (6624)	bewar (11675)	still (18509)	phone (12786)
17	alert (5415)	offens (6624)	item (11672)	late (17730)	refund (12717)
18	knock (5415)	money (6593)	reciev (11556)	wrong (17076)	offer (12412)
19	resel (5225)	bid (6540)	call (11525)	week (16609)	tag (12309)
20	fact (5225)	someth (6406)	tri (11494)	reciev (16319)	model (12044)
21	movi (5225)	reneg (6146)	track (11168)	deliv (16181)	clear (11542)
22	wernt (4739)	sold (6116)	avoid (10695)	up (16030)	open (11280)
23	disney (4739)	avail (5889)	no (10679)	poor (15749)	brand (11071)
24	cheate (4739)	said (5884)	excus (10433)	long (15447)	didnt (11053)
25	trackin (4739)	sell (5731)	lie (10405)	get (14953)	contact (11052)

Table 33: Top 25 Words (Prevalence Scores) by Complaint Type (Group II)

	No Complaint	**Nonspecific**	**Price**	**Quality**	**Return/Refund**
1	thank (100896)	revis (8466)	charg (16467)	broken (30967)	refund (26080)
2	great (77352)	feedback (8339)	overcharg (11613)	work (28451)	return (19210)
3	fast (53277)	problem (7577)	cost (9708)	defect (24692)	money (17699)
4	a (52242)	resolv (7470)	canada (9636)	use (24589)	back (14809)
5	busi (43513)	worst (7359)	sh (8870)	refund (24310)	refus (14459)
6	high (41085)	buyer (6960)	expens (8274)	offer (24210)	polici (12847)
7	you (37368)	luck (6861)	money (8135)	return (24179)	paypal (11096)
8	recommend (37067)	penni (6562)	price (7858)	new (23160)	full (9864)
9	enjoy (32337)	seem (5856)	ship (7577)	damag (21812)	get (9667)
10	gt (32035)	small (5797)	actual (7422)	scratch (21481)	bewar (9524)
11	lt (30608)	issu (5614)	reduc (7059)	contact (21212)	defect (8968)
12	excel (29983)	misunderstand (5492)	outrag (6702)	full (21191)	sent (8824)
13	transact (27746)	thing (5491)	exagger (6702)	bad (17355)	want (8810)
14	revis (26272)	sad (5242)	doubl (6702)	part (16541)	gave (8099)
15	much (25240)	nonpay (5242)	overpr (6702)	batteri (15919)	offer (7989)
16	awesom (24730)	bulli (5242)	paid (5803)	sold (15729)	junk (7839)
17	pleasur (24676)	ethic (5242)	envelop (5681)	miss (15477)	paid (7827)
18	good (23798)	alert (5242)	cent (5681)	crack (15211)	kept (7587)
19	u (23603)	okay (4960)	fee (5458)	open (14772)	wait (7445)
20	glad (23522)	pardon (4639)	rest (5414)	dirti (14565)	wont (7228)
21	again (22584)	aus (4639)	tax (5414)	seal (13853)	fee (7228)
22	posit (22584)	descripit (4639)	whole (5222)	box (13676)	restock (6777)
23	quick (21835)	virgin (4639)	joke (5222)	junk (13452)	broke (6727)
24	welcom (21525)	setup (4639)	save (4849)	phone (13408)	deni (6679)
25	hope (21277)	reslov (4639)	dollor (4738)	warranti (13397)	waiv (6502)

Table 34: Top 25 Bigrams (Prevalence Scores) by Outcome & Satisfaction

	Retained	Returned	Nonreceipt	Positive	Neutral	Negative
1	fast ship (14697)	full refund (21245)	never receiv (21477)	fast ship (42622)	feedback revis (12435)	full refund (27353)
2	thank you (13352)	refund feedback (15404)	cancel transact (19721)	thank you (41902)	revis buyer (12095)	buyer bewar (19253)
3	high recommend (13130)	refund money (15146)	cancel order (19218)	high recommend (35981)	neutral feedback (10297)	bad seller (17741)
4	thank busi (11501)	money refund (11696)	seller cancel (18766)	thank busi (31132)	refund feedback (9296)	never contact (16953)
5	recommend buyer (11122)	got refund (10172)	receiv item (16067)	great seller (30417)	ship bit (7725)	refund money (16246)
6	gt thank (11096)	offer refund (9695)	never got (13720)	lt u (30176)	littl slow (7660)	buyer never (15941)
7	gt lt (11079)	receiv full (9692)	never ship (13278)	gt lt (30134)	leav neutral (7660)	offer full (15851)
8	busi high (11019)	partial refund (9677)	higher price (13257)	gt thank (30019)	ok feedback (6816)	receiv item (15585)
9	lt u (10863)	prompt refund (9443)	cancel seller (12498)	great ebay (29827)	ship cost (6552)	never receiv (15363)
10	u gt (10705)	gave full (9262)	never paid (11738)	recommend buyer (29782)	seller offer (6552)	refund buyer (14979)
11	buyer lt (10688)	seller refund (9230)	won auction (11689)	busi high (29745)	prompt feedback (6425)	money back (14404)
12	great ebay (10358)	refund given (9202)	still receiv (11642)	u gt (29630)	ok ship (6254)	wrong item (12904)
13	great seller (10054)	gave partial (9096)	item never (11152)	buyer lt (29414)	satisfi ship (6254)	partial refund (12799)
14	thank much (9256)	refund product (9096)	sell item (10912)	revis buyer (28924)	bit dirti (6254)	read descript (12726)
15	a a (9068)	gave refund (8773)	never sent (10868)	feedback revis (28737)	slow arriv (6254)	seller cancel (12726)
16	a great (8884)	receiv refund (8262)	price buyer (10821)	thank much (27341)	transact complet (6254)	cancel order (12692)
17	thank great (8376)	refund quick (8005)	item stock (10785)	a great (25966)	refund me (6254)	seller refus (12692)
18	transact thank (8310)	refund still (8005)	never reciev (10277)	a a (25791)	pad envelop (6254)	item sent (12452)
19	seller thank (7880)	issu refund (7966)	pay item (10277)	transact thank (25318)	error part (6254)	negat feedback (12421)
20	thank thank (7769)	refund see (7876)	immedi refund (10277)	seller thank (24888)	product i (6254)	bewar seller (12333)
21	great transact (7699)	wrong item (7249)	paid item (10025)	thank great (23395)	apolog get (6254)	neg feedback (12333)
22	posit feedback (7304)	quick refund (7188)	paid never (9877)	a thank (22518)	appolog error (6254)	poor communic (12333)
23	thank posit (7273)	seller gave (7188)	cancel sale (9859)	ship thank (22418)	paid th (6254)	never ship (12333)
24	ship thank (6929)	item full (6675)	track number (9205)	great transact (21939)	good sell (6254)	buyer want (12007)
25	great ebuy (6924)	mistak refund (6675)	refus ship (9073)	posit feedback (21830)	buyer request (6254)	open case (11996)

Table 35: Top 25 Bigrams (Prevalence Scores) by Complaint Type (Group I)

	None	Nonspecific	Price	Quality	Delivery
1	thank you (41556)	problem feedback (9707)	ship charg (12612)	full refund (20699)	never receiv (21941)
2	fast ship (40346)	right feedback (9282)	money ship (12233)	offer full (15919)	slow ship (19954)
3	high recommend (37846)	revis buyer (8584)	charg money (11700)	broken item (14217)	receiv item (19167)
4	thank busi (32974)	feedback revis (8539)	ship money (10385)	item defect (13610)	item never (17641)
5	lt u (32337)	worst transact (8037)	ship fee (9480)	didnt work (12976)	item ship (16918)
6	gt lt (32334)	thing right (6861)	ship canada (9480)	item work (12947)	ship day (16096)
7	gt thank (32014)	make thing (6861)	paid money (9383)	never contact (12756)	busi day (15146)
8	u gt (31851)	way make (6562)	ship cost (9041)	contact us (12391)	day ship (15021)
9	busi high (31769)	money pleas (6562)	charg ship (8434)	miss part (12149)	track number (14384)
10	recommend buyer (31766)	correct thank (6562)	actual cost (8209)	work seller (12145)	poor packag (13929)
11	buyer lt (31438)	pay never (6562)	actual ship (7053)	work buyer (10894)	item sent (13834)
12	great ebay (29668)	ever buyer (6562)	addit ship (6702)	poor condit (10853)	sent item (13769)
13	great seller (28824)	money extra (6562)	charg doubl (6702)	send back (10767)	post offic (13669)
14	thank much (28464)	feedback buy (6562)	cost clear (6702)	brand new (10483)	took day (12679)
15	feedback revis (26940)	small problem (6562)	charg extra (6702)	keep item (10178)	still receiv (12597)
16	a a (26714)	work out (6047)	canada never (6702)	new seal (9642)	ship within (12518)
17	revis buyer (26713)	resolv problem (5995)	resolv nice (6702)	return item (9520)	day payment (12457)
18	a great (25736)	fix problem (5492)	given multipl (6702)	item damag (9216)	wrong item (12412)
19	transact thank (25208)	seller went (5439)	cost littl (6702)	never gave (9170)	paid item (12292)
20	thank great (24979)	problem thank (5439)	act post (6702)	work proper (9170)	never ship (12292)
21	seller thank (23917)	mistak feedback (5242)	discount given (6702)	request return (9170)	ship took (11107)
22	thank thank (23566)	work quick (5242)	ship expens (6702)	mani scratch (9170)	never arriv (11107)
23	thank posit (22999)	work issu (5242)	charg twice (6702)	wast money (9170)	ship delay (11107)
24	posit feedback (22622)	everi thing (5242)	ship phone (6702)	defect product (9170)	wrong address (11107)
25	great transact (22428)	money within (5242)	ship clear (6702)	sent broken (9170)	ship item (10705)

Table 36: Top 25 Bigrams (Prevalence Scores) by Complaint Type (Group II)

	Cancellation	Misrepresentation	Return/Refund	Black Market	Communication
1	seller cancel (16477)	list new (11363)	get refund (12289)	sell stolen (9482)	bad communic (17330)
2	cancel transact (13741)	read descript (10370)	get money (11747)	give fake (8211)	poor communic (17307)
3	cancel order (13039)	brand new (10363)	money back (11520)	sell fake (8211)	respond email (16187)
4	higher price (12447)	use item (10331)	refus refund (10574)	stolen phone (8211)	respond messag (12303)
5	won bid (10477)	item new (10188)	wait refund (10341)	fake item (8211)	never respond (12225)
6	price buyer (9501)	item descript (10045)	return polici (9876)	fake card (8211)	respons email (11509)
7	order cancel (9370)	item brand (9718)	money refund (9756)	sold stolen (8211)	receiv email (10652)
8	immedi refund (8245)	describ item (9264)	sent back (9453)	dont give (8211)	email seller (10590)
9	cancel seller (8119)	new box (8833)	refund paypal (9290)	fake seller (8211)	seller never (10472)
10	item stock (8119)	use batteri (8648)	full refund (9074)	playerauct right (6703)	communic buyer (10048)
11	buyer notifi (8114)	state phone (8648)	want money (9070)	get fact (6703)	repli email (9723)
12	item higher (8114)	got exact (8648)	return ship (8722)	phone verizon (6703)	deliv buyer (9723)
13	claim item (7524)	describ use (8648)	refund money (8531)	guid bought (6703)	seller rude (9723)
14	relist item (7524)	offer refund (8444)	ship back (8510)	scam took (6703)	repli messag (9723)
15	issu refund (7184)	seller lie (8134)	pay return (8510)	report stolen (6703)	never answer (9676)
16	auction cancel (6949)	item use (8004)	refund buyer (8236)	lie buyer (6703)	answer email (9676)
17	win bid (6949)	item describ (7894)	back use (8119)	stolen item (6703)	ebay refund (8877)
18	seller back (6949)	new describ (7782)	polici clear (7965)	watch movi (6703)	tri scam (8877)
19	cancel sale (6907)	use new (7782)	refund rude (7965)	sent stolen (6703)	email work (8696)
20	won auction (6907)	open item (7782)	give money (7965)	right resel (6703)	reciev email (8696)
21	refus cancel (6624)	full refund (7561)	kept item (7965)	bought playerauct (6703)	answer messag (8696)
22	cancel buyer (6624)	refund return (7553)	still gave (7965)	scam alert (6703)	email sent (8696)
23	cancel due (6624)	didnt work (7553)	take return (7875)	headphon fake (6703)	bad attitud (8675)
24	due item (6624)	condit describ (7553)	seller refund (7702)	sold counterfeit (6703)	seller poor (8675)
25	out stock (6624)	buyer read (7504)	seller refus (7352)	resel get (6703)	seller bewar (8587)

Table 37: Top 25 Trigrams (Prevalence Scores) by Outcome and Satisfaction

	Transaction Outcome			Transaction Satisfaction		
	Retained	**Returned**	**Nonreceipt**	**Positive**	**Neutral**	**Negative**
1	gt lt u (11079)	refund feedback revis (15894)	never receiv item (16309)	gt lt u (30134)	feedback revis buyer (12095)	offer full refund (14356)
2	high recommend buyer (11045)	receiv full refund (9692)	seller cancel transact (11689)	u gt lt (29862)	seller offer refund (9891)	never contact me (10810)
3	busi high recommend (11019)	gave full refund (9262)	seller cancel order (10821)	high recommend buyer (29837)	refund feedback revis (9648)	never receiv item (10156)
4	u gt lt (11002)	gave partial refund (9096)	buyer never paid (8844)	busi high recommend (29745)	leav neutral feedback (7660)	buyer never contact (9465)
5	recommend buyer lt (10993)	full refund feedback (7876)	never ship item (8844)	recommend buyer lt (29653)	prompt feedback revis (7660)	issu full refund (8990)
6	buyer lt u (10993)	item full refund (6675)	receiv item seller (8834)	buyer lt u (29653)	ok feedback revis (6816)	item brand new (8628)
7	u gt thank (10993)	money refund feedback (6430)	never reciev item (8834)	u gt thank (29653)	paid money ship (6425)	brand new seal (8475)
8	thank busi high (10993)	list mistak refund (6430)	buyer pay item (8834)	thank busi high (29653)	honest seller feedback (6425)	get money back (7946)
9	gt thank busi (10993)	buyer partial refund (6430)	never sent item (8028)	gt thank busi (29653)	list mistak refund (6254)	full refund given (7927)
10	lt u gt (10705)	full refund still (6430)	want money back (7712)	lt u gt (29630)	ship littl slow (6254)	seller sent wrong (7927)
11	a a a (9007)	given full refund (6430)	item higher price (7649)	feedback revis buyer (28924)	got paid for (6254)	never sent item (7927)
12	a great ebay (7449)	open miss part (6430)	seller refus ship (7649)	a a a (25582)	seller fault feedback (6254)	seller cancel transact (7927)
13	a a great (7449)	seller gave full (6430)	item want money (7649)	thank posit feedback (21476)	item list use (6254)	sent wrong item (7587)
14	thank posit feedback (7236)	incl full refund (6430)	receiv email seller (7649)	a a great (21078)	correct thank you (6254)	seller cancel order (7338)
15	fast ship thank (6728)	seller tri resolv (6430)	never paid item (7649)	a great ebay (21078)	work item new (6254)	buyer receiv item (7338)
16	thank god bless (6318)	money plus return (6430)	item never receiv (7360)	fast ship thank (20141)	fault feedback revis (6254)	never ship item (7338)
17	hope busi again (6318)	refund still got (6430)	immedi refund money (6413)	thank god bless (18783)	okay feedback revis (6254)	gave full refund (7333)
18	jesss basement enjoy (6276)	item still want (6430)	agre cancel transact (6413)	jesss basement enjoy (18643)	damag seller offer (6254)	receiv full refund (6777)
19	transact thank god (6233)	file claim refund (6430)	item never ship (6413)	transact thank god (18501)	littl slow good (6254)	worst seller ever (6698)
20	basement enjoy pleasur (6060)	refund cost item (6430)	buyer accept cancel (6245)	hope busi again (18224)	concern feedback revis (6254)	seller stay away (6698)
21	much jesss basement (6015)	money refund sent (6430)	item still receiv (6245)	basement enjoy pleasur (17923)	work describ seller (6254)	buyer bewar buyer (6698)
22	thank much jesss (6015)	refund slow ship (6430)	sale claim item (6245)	much jesss basement (17776)	return feedback revis (6254)	read item descript (6698)
23	great transact thank (5604)	instant refund money (6430)	refund money email (6245)	thank much jesss (17776)	refund quick thank (6254)	full refund buyer (6698)
24	thank you enjoy (5461)	seller send item (6430)	lost shipment fedex (6245)	thank you enjoy (17202)	seller respond feedback (6254)	never buy seller (6698)
25	custom high valu (5412)	seller issu refund (6430)	seller back deal (6245)	fast ship great (16398)	free ship buyer (6254)	want money back (6698)

Table 38: Top 25 Trigrams (Prevalence Scores) by Complaint Type (Group I)

	Black Market	Cancellation	Communication	Delivery	Misrepresentation
1	give fake card (8211)	seller cancel transact (10568)	never receiv email (8696)	never receiv item (17147)	item brand new (9718)
2	dont give fake (8211)	item higher price (8114)	ship respond email (8696)	item never receiv (10162)	item list new (7488)
3	sold stolen item (6703)	seller cancel order (7524)	seller poor communic (7530)	took day ship (9385)	pull fast one (7488)
4	resel get fact (6703)	immedi refund money (6949)	sever messag left (7530)	day ship item (9385)	full refund return (7488)
5	right resel get (6703)	buyer accept cancel (6624)	never respond email (7530)	ship within hour (8393)	send item back (6227)
6	guid bought playerauct (6703)	seller honor auction (6624)	never repli messag (7530)	within busi day (8393)	use item new (6227)
7	playerauct right resel (6703)	cancel due item (6624)	receiv email seller (7530)	paid item never (8393)	item describ item (6227)
8	bought playerauct right (6703)	purchas item seller (6624)	seller respons email (7530)	ship within busi (8393)	new seal receiv (6113)
9	messag resort stolen (4739)	item unavail ship (6624)	never reciev email (7530)	item ship time (8393)	match i still (6113)
10	say buyer contact (4739)	won auction seller (6624)	receiv item seller (6275)	item never arriv (8393)	open item new (6113)
11	think make shoe (4739)	buyer want item (6624)	took day pay (6275)	item never ship (8393)	ship sent item (6113)
12	look feedback score (4739)	cancel seller without (6624)	code p vipgxfrwdcch (6147)	ship day payment (8393)	phone use new (6113)
13	imei clean check (4739)	refus sell item (6624)	refund money email (6147)	day payment receiv (8393)	item condit describ (6113)
14	make origin retro (4739)	higher price buyer (6624)	time but get (6147)	never ship item (8305)	tri pull fast (6113)
15	post neg feedback (4739)	seller without explan (6624)	lost shipment fedex (6147)	sent wrong item (7555)	new never open (6113)
16	refund sold someon (4739)	relist higher price (6624)	redeem scamm gave (6147)	never sent item (7446)	buyer return order (6113)
17	vacuum report stolen (4739)	damag car accid (5318)	open case ebay (6147)	usp track number (7268)	phone state descript (6113)
18	given still negat (4739)	seller never ship (5318)	custom suffer lose (6147)	day handl time (7268)	item much wors (6113)
19	mile truck junk (4739)	unkonwn intern issu (4683)	bewar item never (6147)	never contact resolv (7268)	total rip off (6113)
20	wo problem screen (4739)	transact error list (4683)	offerd full refund (6147)	within hour payment (7268)	still refund i (6113)
21	mess off buyer (4739)	back prompt swift (4683)	deliv buyer receiv (6147)	time get here (7268)	seller full refund (6113)
22	get money fraud (4739)	chang ur mind (4683)	fedex track no (6147)	ship one day (7268)	clear state phone (6113)
23	i watch movi (4739)	won item custom (4683)	communic member throughout (6147)	busi day handl (7268)	state brand new (6113)
24	beat fake made (4739)	we tri cancel (4683)	get repli no (6147)	ship bit slow (7268)	brand new just (6113)
25	extrem unreason demand (4739)	still impress error (4683)	messag left unansw (6147)	ship wrong item (7268)	wors condit describ (6113)

Table 39: Top 25 Trigrams (Prevalence Scores) by Complaint Type (Group II)

	No Complaint	Nonspecific	Price	Quality	Return/Refund
1	gt lt u (32334)	problem feedback revis (9707)	paid money ship (9480)	offer full refund (16198)	get money back (11488)
2	u gt lt (32092)	right feedback revis (9282)	ship charg money (8209)	item work seller (8201)	ship wrong item (7965)
3	high recommend buyer (31851)	feedback revis buyer (8584)	ship paid money (8209)	never contact us (8201)	gave full refund (6862)
4	lt u gt (31851)	thing right feedback (6562)	clear state auction (6702)	brand new seal (8178)	pay return ship (6777)
5	busi high recommend (31769)	fix problem feedback (6562)	ship cost littl (6702)	return full refund (7464)	open case get (6777)
6	recommend buyer lt (31687)	correct thank you (6562)	ship cost clear (6702)	item poor condit (7102)	seller sent wrong (6679)
7	buyer lt u (31687)	seller fix problem (6562)	actual ship money (6702)	item miss part (7102)	refund money email (6502)
8	u gt thank (31687)	return refund feedback (6562)	cost clear state (6702)	offer money back (7102)	refund refus ship (6502)
9	thank busi high (31687)	worst transact ever (6562)	ship canada never (6702)	work seller refund (7102)	money refund paypal (6502)
10	gt thank busi (31687)	resolv problem feedback (6562)	money ship paid (6702)	item damag seller (7102)	buyer want money (6502)
11	feedback revis buyer (26713)	make thing right (6562)	ship clear state (6702)	item didnt work (7102)	buyer return address (6502)
12	a a a (26524)	went way make (6562)	left feedback mistak (6702)	custom never contact (7102)	pay ship back (6502)
13	thank posit feedback (22891)	seller got mad (5242)	contact resolv nice (6702)	pleas contact us (6305)	money back refund (6502)
14	a a great (21640)	ran code issu (5242)	seller ask money (6702)	item new box (6092)	final got money (6502)
15	a great ebay (21640)	worst ebay experi (5242)	given multipl item (6702)	brand new item (6092)	return ship buyer (6502)
16	fast ship thank (19355)	issu resolv feedback (5242)	refus ship phone (6702)	issu full refund (5849)	give money back (6502)
17	thank god bless (19165)	mad ran code (5242)	canada never contact (6702)	phone brand new (5798)	refund buyer dishonest (6502)
18	jesss basement enjoy (19036)	refund money within (5242)	relist higher price (6702)	someth that sold (5798)	buyer made mistak (6502)
19	transact thank god (18907)	got mad ran (5242)	discount given multipl (6702)	return broken item (5798)	damag seller refus (6502)
20	hope busi again (18605)	mistak feedback revis (5242)	never contact resolv (5414)	new item defect (5798)	want pay return (6502)
21	basement enjoy pleasur (18381)	honest seller refund (5242)	made mistak ship (5414)	list mislead seller (5798)	payment refund buyer (6502)
22	much jesss basement (18247)	code issu refund (5242)	clear state list (5414)	start wash ahead (5798)	dishonest seller sell (6502)
23	thank much jesss (18247)	within day payment (4639)	within day payment (4738)	use factori seal (5798)	it gave full (6502)
24	great transact thank (17000)	servic will take (4639)	sent back camera (4738)	full refund still (5798)	refus pay return (6502)
25	thank you enjoy (16564)	suppos retrun great (4639)	want pay money (4738)	game scratch up (5798)	get refund sent (6502)

VALIDATION AND PERFORMANCE MEASUREMENT

After each category-specific dictionary was created from the 6,942-review training set, they were applied to a holdout (validation) set to test the validity of the text classification methodology. Each dictionary was used to predict the three tag types (transaction satisfaction, transaction outcome, complaint type) of the 2,500 threads in the validation set. Then, the predicted outcomes of each thread were compared to the results from a second round of human tagging.

Table 40 presents the prediction accuracy for each scoring unit (unigram, bigram, trigram). Overall, the prediction models performed well, with an average of 83.84% and 82.52% agreement across all scoring units with respect to transaction satisfaction and outcome, respectively. The dictionaries also identified the presence of at least one complaint that was matched to the validation set in 87.36% of the threads (on average), and the models correctly identified unexpected outcomes 83.27% of the time.

Table 40: Percentage Agreement with Validation Set across Tag Types

Scoring Unit	Transaction Satisfaction	Transaction Outcome	Unexpected Outcome	Complaint Existence	Average
Unigram	81.69%	78.87%	79.57%	86.70%	81.71%
Bigram	85.11%	83.12%	83.93%	87.81%	84.99%
Trigram	84.71%	85.56%	86.30%	87.56%	86.03%
Average	83.84%	82.52%	83.27%	87.36%	84.24%

Table 41: Complaints, Outcomes, and Service Recoveries by Scoring Unit

Method of Identification	Unexpected Outcomes		Complaints		Service Recoveries	
	Count	Pct. of Valid. Set	Count	Pct. of Valid. Set	Count	Pct. of Complaints
Validation Set Tags	160	6.53%	338	13.78%	174	51.48%
Unigrams	645	26.31%	388	15.82%	41	10.57%
Bigrams	516	21.04%	259	10.56%	71	27.41%
Trigrams	392	15.99%	153	6.24%	71	46.41%

Note: 2,452 unique threads in the validation set

Table 42: Agreement Term Definitions

Term	Definition
True Positives	Actual complaints that were correctly identified
False Positives	Non-Complaints that were identified as complaints
True Negatives	Non-Complaints that were correctly identified
False Negatives	Actual complaints that were not identified

Table 43: Predictive Performance of Compliant Identification

Scoring Unit	True Positives		False Positives	True Negatives	False Negatives	
	Count	Percent	Count	Count	Count	Percent
Unigrams	200	59.17%	188	1926	138	40.83%
Bigrams	149	44.08%	110	2004	189	55.92%
Trigrams	93	27.51%	60	2054	245	72.49%
Total	442	Avg. = 44%	358	5984	572	Avg. = 56%

The bigram and trigram dictionaries dominated the unigram dictionaries across all categories. The trigram dictionary appears to perform best, with the highest overall accuracy (86.03%) and the highest accuracy with respect to transaction outcome (86.30%) and unexpected outcomes (86.30%). The bigram dictionary was nearly as accurate as the trigram dictionary, with an overall accuracy of 84.99% and the highest accuracy in the transaction satisfaction (85.11%) and complaint existence (87.81%) categories. The unigram dictionary performed worst, with an overall accuracy of (81.71%).

Table 41 presents count and percentage measures of unexpected outcomes, complaints, and service recoveries in the validation set and the predicted output of each scoring unit. The taggers identified 160 unexpected outcomes and 338 complaints in the 2,452-tag validation set, respectively representing 6.53% and 13.78% of the distinct threads. Of the 338 complaints, 174 (51.48%) resulted in successful service recoveries.

The predictive performance of the three scoring units varies. As expected, the unigram dictionary identified the most unexpected outcomes and complaints. Single words are rarely distinct enough to identify the context and meaning of the threads. Unigrams also cannot identify words that contradict or alter the terms meaning. For example, “good” may be preceded by “not” which could clearly lead to misclassification of the overall satisfaction.

The unigram dictionary categorized 645 threads (26.31%) into unexpected outcomes, 388 threads (15.82%) as complaints, with only 41 (10.57%) indicating a service recovery. The bigram dictionary predicted fewer unexpected outcomes (516; 21.04%) and complaints (259; 10.56%) than the unigram list, but more service recoveries (71) and a much larger ratio of service recovery to complaints (27.41% versus 10.57%). Finally, the trigram dictionary, which includes the most distinct set of phrases, was the most selective when predicting unexpected outcomes (392; 15.99%) and complaints (259; 10.56%), as expected. While the trigram dictionary predicted the same number of service recoveries as the bigram dictionary, it predicted a much higher percentage (46.41%) of service recoveries relative to complaints. This percentage was also much closer to the actual number of service recoveries tagged in the validation set. The trigram dictionary also predicted the percentage of unexpected outcomes closest to that of the validation set tags; however, it produced the percentage of complaints furthest from the true (tagged) values.

As a final validity check, we evaluate dictionary performance with respect to complaint identification. More specifically, we determine the accuracy based on the number of true positives false negatives. See table 42 for a definition of each measure.

Table 43 summarizes the performance of the three scoring units with respect to the complaints identified in the validation set tags. The count of true positives and the percentage of true positives out of the total complaints in the validation set (381) are listed in the first column. The count and percentage of false negatives are in the final

column. The total true positives (false negatives) and the average true positives (false negatives) across all three scoring units are presented in the final row. The count of false positives and true negatives are listed in the middle columns for reference purposes, and the total for each category is listed in the final row.

The results show that the three methods produced an average 44% true positives and 56% false negatives. The unigram list, which predicted the highest number of complaints, produced the highest percentage of true positives, and the lowest percentage of false negatives. The trigram list, which was the most distinct and selective in its prediction of complaints, produced the lowest percentage of true positives and the highest percentage of false negatives. The bigram dictionary ranked consistently in the middle across the two categories, with 44% true positives and 56% false negatives, identical to the overall average for the three scoring methods.

Based on the motivation of this study: to examine the impact of trust-revoking comments and the impact of service recoveries, the trigram dictionaries were deemed the most accurately predictive of actual outcomes, and they are therefore, used to classify all remaining threads in the holdout set.

PREDICTED OUTCOMES

In the final step of the feedback classification process, the category-specific dictionaries are used to score the remaining feedback posts in the holdout set. The same pre-processing steps previously described are performed on each feedback thread, and

then, each post is assigned an overall prevalence score for each category based on the sum of the prevalence (CC) scores for each matching word from the category-specific word dictionary. The highest sum in each category is designated as the outcome. If none of the outcomes within a category (e.g. positive, neutral, negative) is predicted, then the most conservative value (i.e. positive satisfaction, expected outcome, and no complaint) is assumed. Table 44 summarizes the predicted values of each scoring unit.

Based on the predicted outcomes and expectations based off previous studies, the trigram scoring unit was deemed most appropriate and selected for the analysis. The models were also estimated using the other scoring methods and the results are available upon request. The combination and optimization of the scoring methods and identifiers is an interesting avenue for future research.

These outcome measures were then aggregated to the seller-level to represent the written feedback history of the observed sellers. For sellers with multiple listings, the listing completion date and time are used to identify the feedback history available at the time of sale.

Table 44: Predicted Outcomes by Scoring Unit

	Unigrams		Bigrams		Trigrams	
Field	**Freq.**	**Percent.**	**Freq.**	**Percent.**	**Freq.**	**Percent.**
Complaints						
Complaint-Free Threads	507,813	89.39%	511,838	90.10%	540,328	95.11%
Threads with Complaint	60,296	10.61%	56,271	9.90%	27,781	4.89%
Complaint Types						
Non-Trust Revoking Complaints	799	0.14%	5,644	0.99%	3,229	0.57%
Nonspecific	517	0.09%	3,639	0.64%	2,578	0.45%
Price	282	0.05%	2,005	0.35%	651	0.11%
Trust-Revoking Complaints	59,497	10.47%	50,627	8.91%	24,552	4.32%
Quality	14,630	2.58%	11,647	2.05%	3,668	0.65%
Delivery	27,189	4.79%	15,540	2.74%	4,760	0.84%
Cancellation	928	0.16%	1,738	0.31%	925	0.16%
Misrepresentation	8,790	1.55%	13,945	2.45%	11,166	1.97%
Return/Refund	334	0.06%	2,395	0.42%	1,209	0.21%
Black Market	1,166	0.21%	553	0.10%	396	0.07%
Communication	6,460	1.14%	4,809	0.85%	2,428	0.43%
Service Recovery						
Service Recoveries	9,003	14.93%	18,033	32.05%	9,869	35.52%
Service Recovery Failures	51,293	85.07%	38,238	67.95%	17,912	64.48%
Transaction Outcome						
Expected Outcomes (Retained)	508,338	89.48%	534,227	94.04%	558,568	98.32%
Unexpected Outcomes	59,771	10.52%	33,882	5.96%	9,541	1.68%
Nonreceipt	47,519	8.36%	18,830	3.31%	3,680	0.65%
Returned	12,252	2.16%	15,052	2.65%	5,861	1.03%
Transaction Satisfaction						
Positive Threads	502,386	88.43%	520,110	91.55%	542,954	95.57%
Neutral Threads	1,164	0.20%	9,065	1.60%	7,191	1.27%
Negative Threads	64,559	11.36%	38,934	6.85%	17,964	3.16%

Note 1: Dataset includes 568,109 distinct threads
Note 2: Service Recovery percentages are based on the threads with a complaint

Appendix D: Tagging Instructions and Protocol

TAGGING INSTRUCTIONS

1. Go to pamtag.pamplin.vt.edu
2. Enter your email as your username and enter your unique password.
3. Under "Your Projects" click on the current project.
4. Read the text content in the first column, and then, based on your interpretation of the text, categorize the thread using the bullets and checkboxes in the 2nd, 3rd, and 4th columns. If you are unsure how to tag a post, indicate this using the comments box in the 5th column. Please refer to the Tagging Protocol below for descriptions of each category and example tags.
5. Once you have completely tagged all ten threads, click the Submit button at the bottom left of the screen and repeat step 4 for the next set of tags.

TAGGING PROTOCOL

Transaction Outcome: Tag Type; describes the end result of the transaction.

- For transaction outcome column, tag as follows:

– *Retained* - Buyer kept the product(s).
– *Returned* - Buyer returned the product(s).
– *Refunded* - Buyer kept the product(s) and received a full or partial refund.
– *Exchanged* - Buyer exchanged the product(s).
– *Non-delivery* - Buyer never received the product(s), although seller claims product(s) were shipped.
– *Buyer Cancellation* – Buyer cancelled the transaction prior to the product(s) being shipped.
– *Seller Cancellation* – Seller cancelled the transaction prior to shipping the product(s).

Transaction Satisfaction: Tag Type; describes the buyer's satisfaction with the transaction.

- For transaction satisfaction column, tag as follows:

– *Positive* - Buyer's feedback is generally positive
– *Neutral* - Buyer's feedback is neutral
– *Negative* - Buyer's feedback is generally negative

Complaint Type: Tag Type; describes the buyer's complaint, if any, regarding the transaction.

- For complaint type column, tag as follows:

– *No Complaint* – Buyer does not complain about any aspect of the transaction or product(s).
– *Return/Refund Complaint* - Buyer complains about the seller's process for handling returns or issuing refunds.
– *Delivery Complaint* - Buyer complains that the product(s) arrived late or not at all, had poor packaging, or was the incorrect item.
– *Price Complaint* – Buyer complains that the seller overcharged for the product(s) or shipping.
– *Cancellation Complaint* – Buyer complains that the seller reneged on the transaction.
– *Misrepresentation Complaint* – Buyer complains that the seller was deceptive in their product(s) description.
– *Black Market Complaint* – Buyer complains that the transaction involved some aspect of illegality.
– *Quality Complaint* – Buyer complains that the product(s) is of low quality, broken, defective, or missing an item or part.
– *Communication Complaint* – Buyer complains that the seller was unresponsive, unprofessional, ineffective, or slow to respond to questions or concerns.
– *Nonspecific Complaint* – Buyer indicates the existence of a problem during the transaction but does not provide further detail.

Important Notes:

- Complaint Type is a multiple-select field:

– For Windows, hold down the control (ctrl) button to select multiple options.
– For Mac, hold down the command button to select multiple options.

- Use the comment section if:

– Any of the available tags is not suitable, and/or
– Further information needs to be provided.

- Be careful when tagging posts such as "seller posted item that were out of stock." This is a "Cancellation" not a "Non-delivery."

Example Feedback Posts and Tags:

Example #1
Feedback from the buyer: I was deceived… ----- Reply by the seller: Asked buyer to return item for refund, buyer declined.

How to Tag:

- Transaction Outcome → Retained

- Transaction Satisfaction → Negative
- Complaint Type → Misrepresentation Complaint

Example #2
Feedback from the buyer: Delivered as promised and refunded return without an issue. Prompt communication. ----- Reply by the seller: ;) We work to ensure everyone is 100% SATISFIED feels we've earned 5 STARS!

How to Tag:

- Transaction Outcome → Returned
- Transaction Satisfaction → Positive
- Complaint Type → No Complaint

Example #3
Feedback from the buyer: BEWARE: sent me a broken amp. It cost me $65 to get refund. Basically stole my $ ----- Reply by the seller: A refund was given to buyer less the ship he sent, plus I paid 1/2 new ship.

How to Tag:

- Transaction Outcome → Returned
- Transaction Satisfaction → Negative
- Complaint Type → Return/Refund Complaint & Quality Complaint

Example #4
Feedback from the buyer: Sorry - Item delivered not the one bid on!! - Cannot recommend ----- Reply by the seller: I offered a full refund and still get bad feedback? Thank you ----- Follow-up by the buyer: Total fraud - sends different item then offers, withdraws refund!!

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Misrepresentation Complaint & Return/Refund Complaint

Example #5
Feedback from the buyer: I purchased what was advertised to be BOSE QC25. I contact bose. They're fake. ----- Reply by the seller: I was unaware I accepted the return and started the return process thank you

How to Tag:

- Transaction Outcome → Returned
- Transaction Satisfaction → Negative

- Complaint Type → Black Market Complaint

Example #6
"Feedback from the buyer: I think it is fake. This is slow, over heat quick. Can't really work with it. ----- Reply by the seller: This is 100% genuine Sony product. Please email us, we will help you. Thx."

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Quality Complaint & Black-Market Complaint

Example #7
Feedback from the buyer: This is not new one!! ----- Reply by the seller: Item Was New, I Wouldn't List 8 Used Hard Drives as New, No Contact.

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Misrepresentation Complaint

Example #8
Feedback from the buyer: This item was never delivered to me and the seller never responded to my email. ----- Reply by the seller: USPS made a mistake delivering your package, We have reshipped your package.

How to Tag:

- Transaction Outcome → Non-delivery
- Transaction Satisfaction → Negative
- Complaint Type → Delivery Complaint & Communication Complaint

Example #9
Feedback from the buyer: this very bad item ----- Reply by the seller: Tried hard to scam me! Still have not got the item back to inspect and refund.

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Quality Complaint

Example #10
Feedback from the buyer: This was a great purchase--fast shipping also ----- Reply by the seller: Thank you for the positive feedback!

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Positive
- Complaint Type → No Complaint

Example #11
Feedback from the buyer: Took a very long time to get here for how much it cost. ----- Reply by the seller: Item emailed out within 48 hours after payment; if not received, why no contact?

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Delivery Complaint & Price Complaint

Example #12
Feedback from the buyer: very annoying transaction, money refunded by PayPal ----- Feedback was revised by the buyer.

How to Tag:

- Transaction Outcome → Refunded
- Transaction Satisfaction → Negative
- Complaint Type → Return/Refund Complaint & Nonspecific Complaint

Example #13
Feedback from the buyer: Won the item on August 21 needed the shipping cost never answered in two days... ----- Reply by the seller: Buyer violated purchase terms (US shipping only!) Left negative. Some people....

How to Tag:

- Transaction Outcome → Seller Cancellation
- Transaction Satisfaction → Negative
- Complaint Type → Delivery Complaint & Communication Complaint

Example #14
Feedback from the buyer: Works fine ----- Reply by the seller: Thank you.

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Neutral
- Complaint Type → No Complaint

Example #15
Feedback from the buyer: Would not do business again ----- Reply by the seller: What was the issue? I never got any message from you saying anything was wrong.

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Nonspecific Complaint

Example #16
Feedback from the buyer: Older than listed, bad battery, lock code, worn off silver, told him with n 48hrs ----- Reply by the seller: Very picky buyer, USED=slight wear, NEW battery, 7-day ret policy, kept 10 day ----- Follow-up by the buyer: seller lied, phone has lock code that he does not know battery=6 hrs w no use

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Negative
- Complaint Type → Misrepresentation Complaint, Quality Complaint, & Communication Complaint

Example #17
Feedback from the buyer: ok ----- Reply by the seller: A+A+A+ GREAT EBAYER!!!!!!!!!!!!

How to Tag:

- Transaction Outcome → Retained
- Transaction Satisfaction → Neutral
- Complaint Type → No Complaint

Example #18
Feedback from the buyer: Phone did not work but seller fixed issues and refunded the money. Cooperative ----- Feedback was revised by the buyer.

How to Tag:

- Transaction Outcome → Refunded
- Transaction Satisfaction → Positive
- Complaint Type → Quality Complaint

Appendix E: Full Correlation Matrix for Essay 1

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Landed Price	1													
2	Time to Sale	**0.17**	1												
3	Description Length	**0.10**	**0.12**	1											
4	Images	**0.03**	**0.11**	**0.08**	1										
5	Previously Sold	0.02	**0.22**	**0.10**	-0.01	1									
6	One TB HDD	**0.22**	**-0.04**	**0.16**	**-0.04**	**0.03**	1								
7	Kinect	**0.23**	0.02	**0.16**	-0.02	**-0.06**	**-0.08**	1							
8	Weeks from Launch	**-0.14**	**0.05**	**0.20**	**0.03**	**-0.04**	**-0.36**	**0.44**	1						
9	Preorder	**0.10**	-0.02	**0.03**	-0.01	**0.05**	**0.29**	0.00	**-0.18**	1					
10	Seller Tenure	0.02	0.01	**0.16**	0.00	0.00	**-0.03**	**-0.02**	**0.03**	-0.01	1				
11	Percent Positive	0.00	**0.05**	**0.06**	**0.05**	**0.05**	0.02	**-0.10**	**-0.04**	-0.01	**0.13**	1			
12	Percent Negative	**-0.03**	**-0.05**	**-0.06**	**-0.09**	**0.02**	0.00	**0.08**	0.01	0.00	**-0.09**	**-0.40**	1		
13	Log Positive	**-0.05**	**0.10**	**0.40**	**0.10**	**0.14**	**0.08**	-0.01	**0.04**	**0.02**	**0.24**	**0.16**	**-0.17**	1	
14	Log Negative-Neutral	**-0.08**	**0.07**	**0.24**	**-0.06**	**0.03**	-0.01	**0.05**	**0.05**	-0.02	**0.24**	-0.02	0.02	**0.75**	1
15	Returns Allowed	0.01	**0.07**	**0.39**	**0.11**	**0.13**	**0.12**	**0.02**	**-0.03**	**0.04**	**0.10**	**0.07**	-0.02	**0.43**	**0.28**
16	Shorter Window	0.01	0.00	**0.02**	0.00	0.00	-0.01	0.00	-0.01	0.00	0.01	0.00	0.00	0.01	0.03
17	Default Window	0.00	**0.05**	**0.28**	**0.09**	**0.09**	**0.13**	0.00	**-0.06**	**0.05**	**0.07**	**0.06**	-0.02	**0.32**	**0.11**
18	Extended Window	**0.03**	**0.07**	**0.28**	**0.05**	**0.11**	**-0.03**	**0.06**	**0.08**	-0.01	**0.07**	0.02	0.01	**0.29**	**0.34**
19	Free Return Shipping	**0.06**	**0.05**	**0.26**	-0.01	**0.04**	-0.01	**0.08**	**0.11**	-0.01	**0.11**	0.01	-0.01	**0.26**	**0.39**
20	Restocking Fee	**0.03**	**0.10**	**0.24**	**0.10**	**0.08**	0.00	**0.07**	**0.08**	**-0.02**	0.02	**0.05**	**-0.05**	**0.22**	0.01
21	Restock 10%	0.01	**0.04**	**0.06**	**0.06**	**0.06**	**-0.04**	0.01	**0.04**	-0.02	**0.03**	**0.02**	-0.01	**0.10**	**0.04**
22	Restock 15%	0.00	**0.06**	**0.09**	**0.06**	**0.05**	**-0.04**	0.01	**0.04**	-0.01	0.00	**0.03**	**-0.03**	**0.08**	0.00
23	Restock 20%	**0.03**	**0.06**	**0.21**	**0.04**	0.02	**0.05**	**0.08**	**0.05**	-0.01	-0.01	**0.04**	**-0.04**	**0.17**	-0.02
24	Restock Other	0.01	**0.04**	**0.06**	**0.03**	**0.03**	0.00	0.00	-0.01	-0.01	**0.05**	0.01	-0.01	**0.04**	0.01
25	Overnight Shipping	0.00	**-0.02**	**-0.06**	0.00	-0.01	**-0.03**	-0.02	**-0.05**	-0.01	**-0.04**	-0.01	0.02	**-0.06**	**-0.04**
26	Expedited Shipping	**0.04**	**-0.05**	**-0.19**	**0.03**	**-0.08**	**-0.14**	-0.01	**0.05**	-0.01	**-0.14**	**-0.03**	-0.02	**-0.23**	**-0.26**
27	Standard Shipping	**-0.03**	**0.06**	**0.15**	**-0.04**	**0.09**	**0.11**	0.01	0.01	-0.02	**0.11**	**0.04**	-0.02	**0.21**	**0.17**

	Variable	15	16	17	18	19	20	21	22	23	24	25	26	27
15	Returns Allowed	1												
16	Shorter Window	0.02	1											
17	Default Window	**0.92**	-0.02	1										
18	Extended Window	**0.21**	0.00	**-0.18**	1									
19	Free Return Shipping	**0.12**	0.00	**-0.06**	**0.46**	1								
20	Restocking Fee	**0.34**	-0.01	**0.32**	**0.05**	0.01	1							
21	Restock 10%	**0.18**	0.00	**0.15**	**0.09**	0.01	**0.53**	1						
22	Restock 15%	**0.14**	0.00	**0.13**	**0.03**	0.00	**0.43**	**-0.02**	1					
23	Restock 20%	**0.23**	0.00	**0.24**	**-0.02**	0.01	**0.67**	**-0.04**	**-0.03**	1				
24	Restock Other	**0.06**	0.00	**0.06**	-0.01	-0.01	**0.17**	-0.01	-0.01	-0.01	1			
25	Overnight Shipping	**-0.04**	0.00	**-0.03**	-0.02	-0.01	**-0.03**	-0.02	-0.01	-0.02	0.00	1		
26	Expedited Shipping	**-0.20**	-0.02	**-0.17**	**-0.08**	**-0.10**	**-0.05**	**-0.10**	0.00	0.02	0.01	**-0.09**	1	
27	Standard Shipping	**0.12**	**0.03**	**0.07**	**0.11**	**0.11**	**0.05**	**0.09**	0.02	-0.01	0.01	**-0.06**	**-0.72**	1

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